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DEVELOPMENT OF THE INFORMATION TECHNOLOGY FOR DECISION MAKING SUPPORT WHEN MANAGING REFRIGERATION UNITS

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Досліджено особливості процесу прийняття рішень стосовно управлінського впливу з боку оператора холодильної установки, як багатофакторної енергетичної системи із внутрішніми та зовнішніми збурювачами.

Такий об'єкт, як холодильна установка, не може бути у повній мірі формалізований і описаний методами традиційного моделювання, оскільки має властивості часткового саморегулювання та самовирівнювання. Тому на основі застосування узагальненої моделі холодильної установки, вдосконалено систему підтримки прийняття рішень, що дозволяє врахувати неформалізовану інформацію засобами нейро-нечіткого компонента. Розроблено інформаційну технологію підтримки прийняття рішень при керуванні холодильними установками різного типу. Її впровадження дозволяє зменшити час виходу на потрібний режим роботи устаткування та стабілізації температурного режиму в об'єктах. Це дозволяє знизити коефіцієнт робочого часу холодильного устаткування та знизити вплив людського фактору, що підвищує безпеку роботи енергоустановки. Ефективність технології експериментально досліджено на одноступінчатій паро-компресійній промисловій аміачній холодильній установці, одноступінчатій паро-компресійній фреоновій холодильній установці центрального кондиціонера та на водо-аміачному абсорбційно-дифузійному агрегаті побутового морозильника типу «ларь». Кількість збуджуючих факторів та факторів впливу змінювались в широкому діапазоні. Вибірки даних, що призначені для навчання нейро-нечіткої системи, приймались за результатами дослідів на діючому обладнанні.

Запропонована інформаційна технологія може бути використана для створення комп'ютерних тренажерів для підвищення компетентності та кваліфікації промислово-виробничого персоналу без стажування на об'єктах підвищеної небезпеки

Ключові слова: інформаційна підтримка прийняття рішень, інтелектуальне управління холодильним устаткуванням, нейро-нечітке моделювання

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1. Introduction

The process to manage complex technical systems (CTS), which include modern refrigeration units, is associated with the application of decision support procedures. However, the specificity of CTS is typically reflected by the information technology that is developed for a specific class of systems. Therefore, managing modern refrigeration units, considering a permanently relevant task to enhance the effectiveness of their operation, needs improvement. Improvement is needed both for the automated systems to control such units and the information technologies that are developed to support decision-making.

Refrigeration units are related to the objects with increased risk through the use of hazardous substances. The process of control over refrigeration units is typically partially automated, but a significant proportion of decisions is taken by service staff – the operators of refrigeration units. According to research, about 60 % of accidents at the facilities of increased danger is the fault of the staff, and more than 30 % of failures at various sites is due to human factor [1]. The occurrence of an emergency and its subsequent development during operation of a refrigeration unit can be caused by the operator's weakening attention (the human factor). The likeliest reasons may also include random factors that are related to the operational reliability of protective automated devices or their failure.

Information technologies that are aimed to support decision-making contain tools that help employees at enterprises make their decisions. In most cases this makes it possible to provide information support to decision-makers. In addition, information support is one of the essential means that make it possible to automate fully or partially the process of development of managerial influences. Therefore, the implementation of information technologies as an automated tool to manage CTS makes it possible to reduce the number of emergency and near-emergency situations, as well as improve operational indicators of equipment. By applying information systems and related technologies, organizations can improve business decision making and quality of service, or to increase efficiency, productivity, and, accordingly, to increase profit [2].

Development of specialized information support in the form of an integrated information technology that is part of the automated control system of a refrigeration unit, which is aimed to provide information support for decision-making related to managerial influence, is a relevant task.

Thus, improving the automated control system of a refrigeration unit based on the development of an information technology to support decision making can be considered the relevant field of research.

2. Literature review and problem statement

Modern systems that support decision making by an operator are based on classic principles described in papers [3–8]. Study [3] described a model that implies three components in the activities of an operator, for the case of interference in the management process: identifying an event, diagnosing the reasons that caused the identified event, and compensation for consequences. The process of identification is described both from the viewpoint of filtering the information observed by an operator and from the position of recognizing the symptoms of the occurred event. In simple cases, an operator acts as an observer, if the object is complex, as is the case of refrigeration units, the operator acts by referring to procedures for the meaningful analysis of situations. Diagnosing the causes of a dangerous situation may be performed based on regulatory procedures, or through the mechanism of choosing the sequence of actions. Compensation for the consequences of a dangerous situation may be performed based on symptoms or errors. The symptomatic of processes is divided into warning (pre-emergency) and emergency. In this case, while known emergency symptoms may be treated using standard procedures, then deviations from a normal mode may require non-standard actions by the operator. In those cases when the stage of diagnosis is brought to detecting specific abnormalities in the process, a compensation for errors is possible. Such compensation comes down either to the elimination of the identified disorder, or to a transition to the new mode of operation, which rules out the use of a faulty element. However, such an approach does not make it possible to develop an information technology that would be universal for different configurations of refrigeration machines.

Paper [4] presented a model of decision-making approval that is based on a multilevel principle, where levels are skills, rules, and knowledge. The approach, proposed in [4], implies that the operator modifies his behavior by receiving signals both from a controlled object and the purpose of control. That is, the specified feedback operates not only the physical phenomena in the managed object, but the motives behind the operator's activities, namely the experience of his previous behavior or experience by other operators and experts. Similar findings were obtained by the cognitive school of decision making under conditions of uncertainty. In other words, gaining knowledge from experience is based, above all, on defining the relations "action – result" [5], and the interpretation of experience is based on studying causal relations and arrangement of events in the causal scheme [6]. However, the specified approach is costly due to the necessity of engaging a group of experts. In addition, the cognitive approach is associated with subjective considerations by experts, which in systems with a complex configuration may be unsatisfactory. Such an approach was proposed in [7]. In this case, a task for the operator is divided into management, decision making, and others. Each intersection between the level and the stage is assigned with the operator's activities. For example, categorization by context accepts the recognition of images and analysis of observations, planning by structure – the development of a plan and the adaptation, and implementation by state – stereotype automated control. However, this approach is associated with the necessity for a preliminary detailed description of all possible situations that may arise. However, it is not effective in terms of forming a unified model of management taking into consideration the different groups of factors.

A subsystem of making decisions by an operator, described in [8], is part of an overall model of optimal management and includes units of observations, evaluation of situations, selection and implementation of procedures. Paper [9] gives a modern review of analytical models for detecting and diagnosing disorders in the course of a technological process.

However, the active application of such models when studying an operator as an automated observer, appraiser, and optimal "solver" did not contribute to meaningful understanding of the mechanism of decision making.

In paper [10], author notes that the term "decision-making support" was expanded to cover more types of technical support and include the systems that include business analytics and interact with the person who makes decisions. Analytical methods that involve the methods of artificial intelligence create conditions for solving the problem associated with handling the so-called "big data". Methods of artificial intelligence are often chosen to represent and solve such complex problems; a combination of artificial intelligence and approaches to decision support leads to the creation of IDSS (intelligent decision support systems). These systems can be embedded in the work space and are more closely related to styles of decision-making by users and the issue on decision-making itself [10].

Study [11] reports results of research into the application of VIKOR method to solve multi-criteria problems on decision-making that contain conflicting parameters. A decision maker tries to obtain a solution that is most close to perfect by assessing alternatives according to all established criteria. It is shown that it is expedient to use linguistic values to evaluate ratings and weights for these factors, which are notated in the form of trapezoidal or triangular fuzzy numbers. A given strategy is used to solve the tasks on choosing suppliers in a supply chain system. There are prerequisites to consider that such an approach could be applied to improve decision support systems in the field of refrigeration equipment, however, this issue remains unresolved.

Paper [12] examined the application of an approach to solving the problem of decision making based on the algorithm for defining consensus based on the overall value by using a cost function, based on application of the theory of games. The task was solved by using the binary encoding of a genetic algorithm (GA) and Nash-GA. The authors obtained a good result from applying the approach to solve a multi-criteria problem, but such an approach that employs modern methodologies has also lacked verification in the field of managing refrigeration units.

Refrigeration units differ by type and configuration. Typically, models and technologies to manage and support decision making on refrigeration units are constructed for a specific refrigeration unit and cannot be used for units of another type or configuration. Thus, study [13] reports a structure, based on the Information Gap Decision Theory (IGDT), to reliably plan an ice storage system, which consists of a heat pump with air source (ASHP). IGDT is aimed at minimizing the total cost of the energy system that stores ice, at evaluating reliability and possible aspects of optimal operating strategies for decision making under conditions of uncertainty. Paper [14] investigated a vapor-compression refrigeration machine with a cooling tower in order to optimize for multiple criteria. The paper gave an example of the process of decision making for selecting the final decision from a Pareto border. Work [15] proposed an optimization approach, based on knowledge, applied to a single system of a mixed refrigerant (MR), and a MR system with preliminary cooled propane for the liquefaction of natural gas. In addition, in order to optimize energy-efficient design, the authors considered the maximization of efficiency of using a heat exchanger. Study [16] examined the issue on finding the optimal solution depending on the type of a unit and the refrigerant used. The authors described a method to choose performance of the condenser for refrigeration units, as well as a system of control over the level of oil at compressors. Papers [13–16] confirm the existence of a large number of different models, as well as the lack of a general model and universal technology, which could make it possible to use it at installations of different types. The reason for this may be the complexity of processes that occur in refrigeration units, their diversity, a high degree of uncertainty, all of which makes research long and costly, but emphasizes the need to undertake it.

Numerous studies established that neural networks are a useful tool in the design of cooling and air conditioning systems aimed at improving efficiency [17]. In addition, there is a growing body of research into the use of fuzzy neural networks in the field of refrigeration machines and air conditioning. For example, paper [18] describes a model of the fuzzy neural network for an air conditioning system in a car in order to predict cooling capacity, power consumption by the compressor, and efficiency of the system of automotive air conditioners. The values derived to fit actual experimental data indicate that the proposed model produces a high-accuracy prediction for automotive air conditioning systems.

Therefore, one can argue that it is expedient to undertake a research aimed at improving a decision support system in the management of refrigeration units of various types by developing an information technology that would include an intelligent neuro-fuzzy component.

3. The aim and objectives of the study

The aim of this study is to develop a general information technology that would enable supporting a decision-making process by persons exercising control over various industrial refrigeration units in order to improve the qualitative and quantitative indicators of control.

To accomplish the aim, the following tasks have been set:

– to improve a method for the generalization of a refrigeration unit;

– to improve a decision support system for an operator at industrial refrigeration units;

– to improve a model of intelligent support to form managing influences based on a neuro-fuzzy component;

– to design a structural diagram of the information technology to support decision-making when managing refrigeration units.

4. Materials and methods to improve the process of decision-making support when managing refrigeration units

4. 1. Improvement of the method to generalize a refrigeration unit

According to a generally accepted classification [19], refrigeration units differ by purpose, performance, temperature mode, the kind of a refrigeration agent, the technique to obtain cold and low temperatures, the type of energy and the number of elements included in a unit. There are vapor-compression, gas, absorption, vapor-ejection, and thermoelectric refrigeration machines.

All elements that are included in units of different types can be conditionally divided into 4 types:

1 – a source of excess potential linked to the external compensating process;

2 – a collector-heat diffuser linked to the external environment;

3 – a high-to-low potential transformer;

4 – a collector-heat absorber linked to a cooled object.

By using a method of generalization proposed in [20], one can generalize a refrigeration unit and represent a structural-functional scheme of the generalized refrigeration unit of arbitrary configuration (Fig. 1). Colors in the scheme mark the types of units according to their purpose. Gray color marks the elements related to forming a driving force to enable the progress of processes in the energy system due to the external compensating process. Red color marks the elements related to operation under pressure, the high temperature elements, and the elements that are related to the scattering of heat. Blue color marks the elements identified by a standard system as the devices operating under low pressure and temperature. Green color marks the elements that are associated with converting the system's high potential into low independent of the type of conversion or the loss of high potential.

In most cases, refrigeration machines are a closed system working by a reverse thermodynamic cycle. The cyclical nature of operation implies that the system returns to its original state at the end of each individual cycle. The only exception is a separate type of gas machines, which employ atmospheric air as a working substance and can work in an open-loop cycle. However, such units are extremely limited under modern production. Should no other types of refrigerating machines be considered, their functional diagram could be represented in the form of the four above-specified elements. Such an approach has not been used up to now, which led to complications when modeling the operation of units in a complex using the tools of accurate modeling.

In paper [20], the method was tested by verifying it only at a vapor-compression refrigeration unit. The results reported reflect reducing the elements of refrigerating units of various types to a generalized form. By reducing the generalization to the structural-functional diagram shown in Fig. 1, the key elements of the above types of refrigerating machines are categorized as it is given in Table 1.

Table 1

Reducing basic elements of refrigerating machines based on different operation principles to the generalized structural-functional scheme

No. of conditional element	Purpose of conditional element	Analog of conditional element in existing refrigeration machines with different principle of operation				
		Vapor-compression machines	Gas machines	Absorption machine	Vapor-ejection machine	Thermo-electric machine
1	a source of excess potential linked to the external compensating process	compressor	compressor	generator	generator	conductor with the excess number of positively charged particles
2	a collector-heat diffuser linked to the external environment	condenser	hot heat exchanger	condenser+absorber	condenser	hot junction of conductors
3	a high-to-low potential transformer	throttle	adiabatic dilator	throttle	throttle	conductor with the excess number of negatively charged particles
4	a collector-heat absorber linked to a cooled object	evaporator	heat exchanger-refrigerator	evaporator	evaporator	cold junction of conductors

Thus, the proposed method could be used in the development of an information technology for decision making related to managing refrigeration units based on different principles of operation, cooling capacity, and purpose.

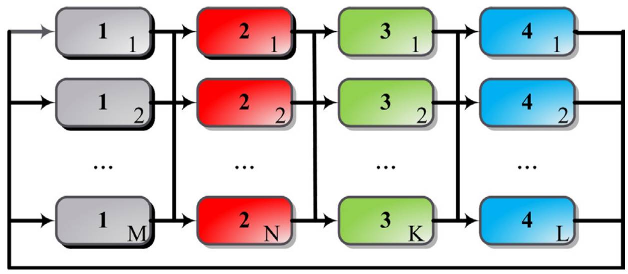

Fig. 1. Structural-functional scheme of the generalized refrigeration unit of arbitrary configuration

4. 2. Improving the system to support decision making by an operator

Operation of any energy systems in general, and specifically refrigeration units, is described not only by the laws of heat-and-mass exchange, heat transfer and dynamics, but also by the protocols that define operators' actions in different situations.

Operation process of a refrigeration unit includes four stages: start, entering a mode, maintaining a mode, disabling the unit. At all these stages, it is required to support operator decisions to execute the task on control.

A decision support system when managing a generalized refrigeration unit includes the following elements:

*U*1 – forming a managing influence in order to control filling the system with a refrigerating agent by transforming high potential into low;

*U*2 – forming a managing influence in order to control the feed of a refrigerating agent to a cooled object;

*U*3 – forming a managing influence in order to control the number of sources of excess potential by enabling and disabling them;

*U*4 – forming a managing influence in order to control the feed of a cooling substance to a heat diffuser (two-way control);

*U*5 – forming a managing influence in order to control the number of the enabled heat diffusers necessary for the system (two-way control);

*U*6 – forming a managing influence in order to prevent an emergency.

The improved scheme of the system to support decision making by an operator is shown in Fig. 2.

The improvement of a decision support systems is that DSS forms a reference control action using the model of intelligent support to form managing influences based on a neuro-fuzzy component, trained on a training dataset from the respective type of a unit. That makes it possible to provide for its property of universality. In addition, the system was supplemented with a unit to define the stage of management. Thus, generation of a reference control action takes into consideration the stage in the operation of the system.

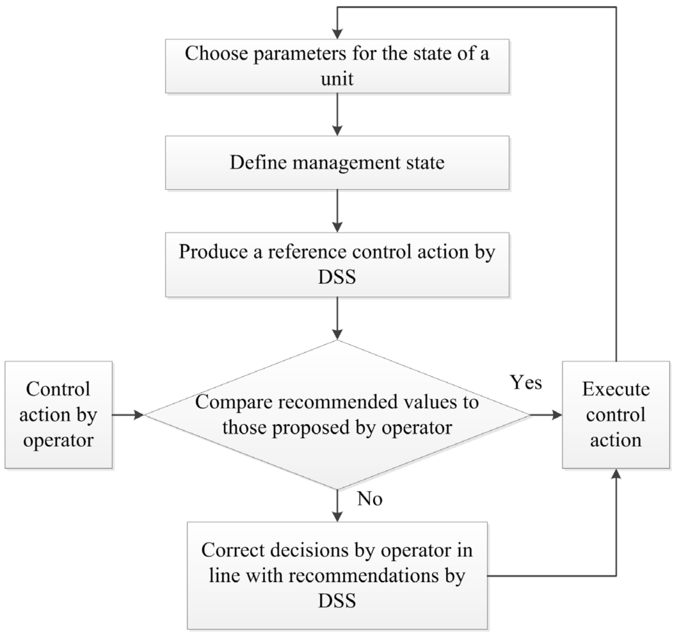

Fig. 2. Scheme of the system to support decision making by operator

4. 3. Improving a model of intelligent support to the formation of managing influences based on a neuro-fuzzy component

The intelligent component of the decision support system implies the formation of reference managing influences for each component within the system by using the model whose structure is shown in Fig. 3.

Such a structure of the model for intelligent support to the formation of managing influences was designed in order to manage the generalized vapor-compression refrigeration machine. In the current study, this structure has been improved by optimizing the number of input and output elements at each unit. During optimization, we considered that the model is intended to manage refrigeration units of different types.

Colors in Fig. 3 denote correspondence between the model's units and the units at the scheme for the generalized refrigeration unit (Fig. 1). Yellow color marks the unit that forms a managing influence to prevent an emergency.

The dynamics of change in the number of the system's elements predetermine a great degree of uncertainty at decision making. Given the complexity and fuzziness in its certain parameters, we have chosen, to implement the model, neuro-fuzzy simulation [21].

Each model's unit *U*1–*U*6 is a direct signal propagation neural network of the ANFIS model (Fig. 4). Such a hybrid network is a system of fuzzy inference the type of Sugeno in which each rule of fuzzy products has a weight of 1. Using it sets the fuzzy parameters. The adaptive neural network performs auto-adjustment of a rule database using the sample of values for the object's parameters. It changes the rules in accordance with the values provided by the training sample in order to bring the process parameters to permissible quality indicators.

All neuro-fuzzy elements of the model were constructed using the software package Fuzzy Logic Toolbox from the system MATLAB [22]. To compile the training and testing samples, we employed experimental data obtained from analyzing daily logs of the operation of actual equipment (Fig. 5).

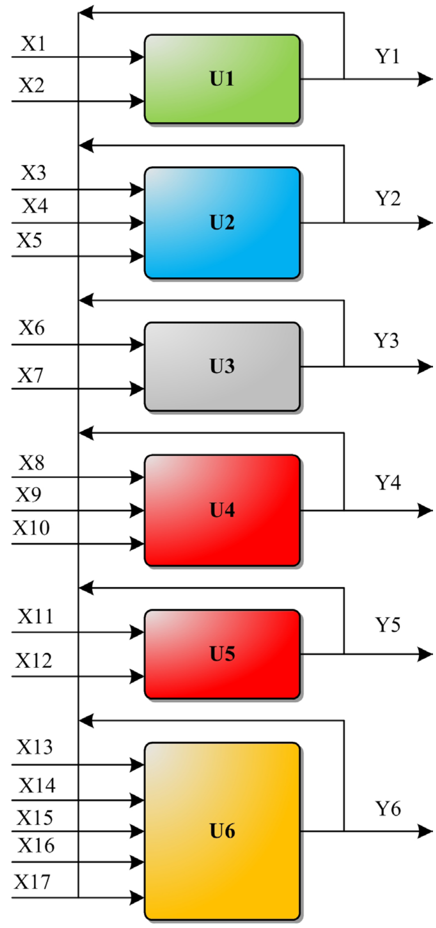

Fig. 3. Structure of the model for intelligent support to the formation of managing influences based on a neuro-fuzzy component: *X*1, *X*3, *X*14 – temperature in a cooling object; *X*2, *X*17 – temperature at the input to a high-to-low potential transformer; *X*4, *X*5 – permissible minimum and maximum values for temperature in a cooling object; *X*7, *X*8, *X*11, *X*15 – temperature in a collector-heat diffuser; *X*12 – ambient temperature; *X*13 – cooling capacity; *X*16 – temperature at the output from a high-to-low potential transformer; *Y*1 is the degree of opening a high-to-low potential transformer; *Y*2 – enabling or disabling an object of cooling; *Y*3 – number of connected sources of excess potential; *Y*4 – number of cooling elements at collectors-heat diffusers; *Y*5 – number of collectors-heat diffusers, *Y*6 – recommendation for preventing an emergency

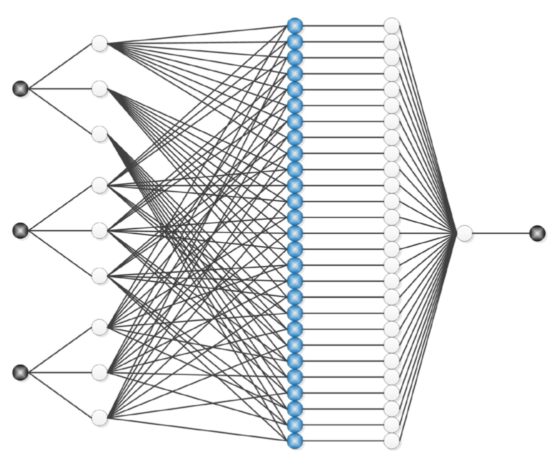

Fig. 4. Structure of the neural network *U*4

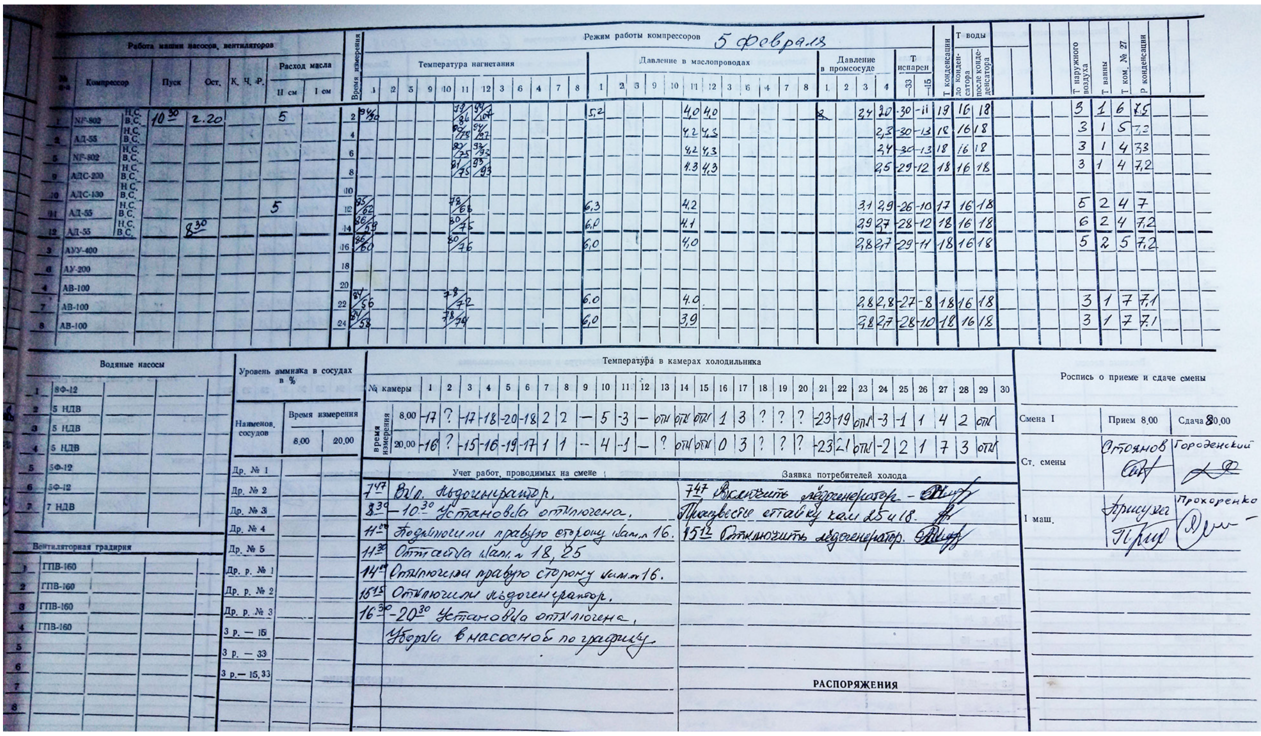

Fig. 5. Log of daily operation of refrigerating equipment

Daily logs containing parameters over a year from the ammonia one-stage vapor-compression refrigeration machine at the meatpacking plant "EREMEEVSKYI MIASOKOMBINAT" (Odessa, Ukraine) (Fig. 6) were taken as a base. The basis for our study was the annual observations and research under conditions of the non-heated and non-chilled lab at the absorption water-ammonia trade-household refrigerator the type of an island freezer (Fig. 7).

Element 1 (Fig. 6) is the source of excess potential for a given system related to the external compensating process. For a given system, elements 5 and 6 (Fig. 6) is the collector-heat diffuser linked to the external environment. For a given system, element 8 (Fig. 6) is the high-to-low potential transformer. For a given system, element 10 (Fig. 6) is the collector-heat absorber linked to a cooled object. This corresponds to the purpose of basic elements in the generalized unit (Fig. 1). Elements 2, 3, 4, 7, 9 (Fig. 6) are not included in the generalized circuit (Fig. 1), because they are not involved in the processes related to the basic cycle of a given refrigeration unit.

Elements 1, 8, and 10 (Fig. 7) in combination are referred to as the thermochemical compressor. These elements form the source of excess potential, associated with the external compensating process. For a given system, elements 3 and 4 (Fig. 7) are the collector-heat diffuser linked to the external environment. For a given system, element 5 (Fig. 7) is the high-to-low potential transformer. For a given system, elements 6 and 7 (Fig. 7) are the collector-heat absorber linked to a cooled object. This corresponds to the purpose of basic elements of the generalized unit (Fig. 1). Auxiliary element 2 from the absorption refrigeration unit (Fig. 7) is not included in the generalized scheme.

Thus, the generalization of the specified units has resulted in the four functional elements (Fig. 1) and two additional control elements (Fig. 3).

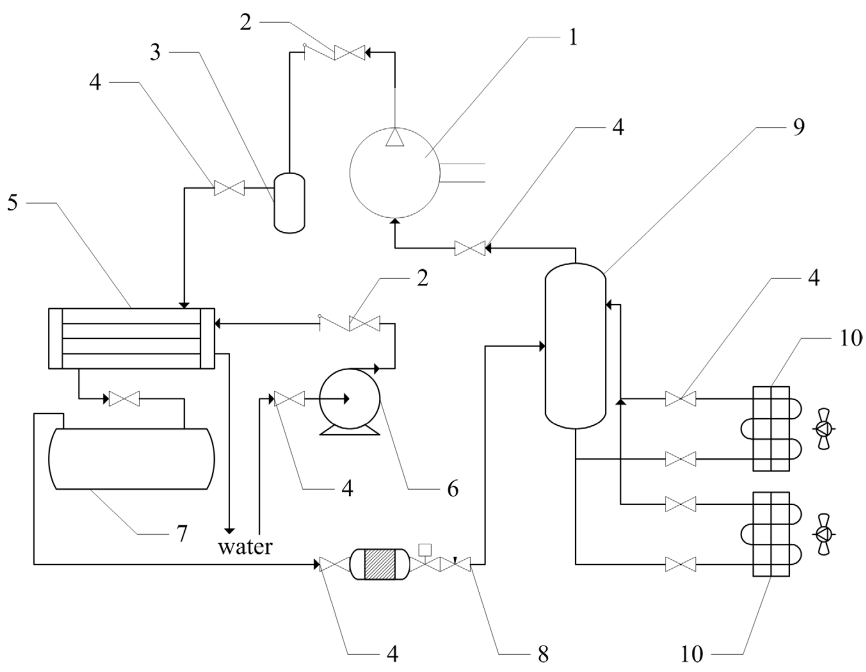

Fig. 6. Circuit of ammonia one-stage industrial vapor-compression refrigeration machine: 1 — compressor; 2 — gate-reverse fixture; 3 — oil separator; 4 — gate valve fixture; 5 — condenser; 6 — water pump; 7 — line receiver; 8 — needle control valve (throttle device); 9 — liquid separator; 10 — evaporator

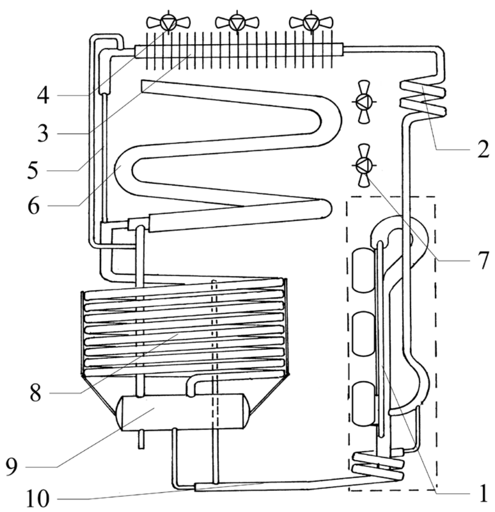

Fig. 7. Absorption water-ammonia commercial-household refrigerator type "Chest" for two units: 1 – generator unit with several heaters in the assembly; 2 – deflegmator; 3 – condenser; 4 – fan; 5 – capillary tube (throttle device); 6 – evaporator; 7 – fan; 8 – absorber; 9 – a linear receiver; 10 – thermosyphon return tube

The linguistic variables that describe the input and output model's parameters are represented by the triangular membership functions and are defined at term set $V=\{NS, Z, PS\}$, where *NS* is the "small value", *Z* – "average value", *PS* – "large value". For each network *U*1–*U*6, experts compiled the initial rule base in the form IF (*X*8 is *NS*) THEN (*Y*4 is *Z*), which is refined when neural networks learn by employing experimental data. The network was trained using a hybrid method. Hybridization was performed based on a combination of the least square method and the method of error back propagation. Training was conducted over 40 cycles. At the stage of training that was implemented using the Fuzzy Logic Toolbox from the MATLAB system, we obtained errors from training and testing the model's elements *U*1–*U*6 in the range of 1.78~1.89. A learning/testing error is calculated as mean square deviation between the results of fuzzy inference and the values for an output variable from a training/testing sample. The value of error is measured in units of the respective output variables *Y*1–*Y*6. The relatively small values of errors indicate compliance of the model to practical needs.

The study results were verified at the actual one-stage ammonia refrigeration machine and at the absorption water-ammonia refrigeration machine, whose experimental data underlie the model's training and testing samples (Fig. 6, 7). Testing was conducted both under a semi-automatic mode, involving an operator, and under an automated mode. Both units were located at the same region, which allows us to argue that the starting conditions for their operation were the same. The temperature modes of cooling objects, maintained by the refrigeration systems of both types, were also the same.

5. An information technology to support decision making when managing refrigeration units

Based on the improved methods and models described above, we have developed a new information technology to support decision making when managing refrigeration units of various configurations (Fig. 8).

All information processes that occur during operation of the information technology proceed in 5 stages, each having 2 to 4 components.

Stage 1. Preparation. At this point, the type of a unit is defined. Next, by using the generalization method, the generalization of a refrigerating unit is performed. This is followed by the downloading of experimental data, splitting the data into a training and a testing sample, and training the neuro-fuzzy management model.

Stage 2. Support the process of start-up. Operation of the unit starts by enabling it. An operator performs the procedures of start; the system supporting decision-making by an operator is enabled: it helps the operator perform proper actions in the launch process. Provided all procedures were conducted properly and the unit was successfully launched, there is a transition to the next stage, otherwise correction activities are carried out.

Stage 3. Support the process of entering a temperature mode. At this stage, the operator performs actions that contribute to the unit entering the required temperature mode. The operator's activities are adjusted by using the DSS. If the unit enters the preset mode, there is a transition to the next stage.

Stage 4. Support to the process of maintaining a temperature mode. This is the longest and the most important Stage in the operation process of a refrigeration unit. At this stage, an operator monitors performance of the unit. Should the parameters deviated from those permissible, the operator performs corrective actions that contribute to bringing the unit back to the required temperature mode. The actions of the operator are adjusted using the DSS. If a scheduled or emergency stop of the equipment is needed, there is a transition to the next stage.

Stage 5. Support to the process of termination. At this stage, the operator performs termination procedures using the DSS. If all procedures were conducted properly and the unit was successfully stopped, the process ends.

The developed information technology was implemented at the computer simulator for training operators for refrigeration units IceQueen. A given simulator was designed by Authors at the initial stages of the current study. A functional diagram of the simulator is shown in Fig. 9. It outlines the structure and features of interface at the simulating system. A new version of the simulator contains the updated and improved model to support decision-making by an operator. In the future, we plan to improve the interface of the simulator using more modern design tools.

The tests that followed the introduction of the information technology have shown that a working time factor (WTF) for refrigeration equipment decreased on average by 2.7 %. That testifies to the increase in the energy efficiency of the unit. Values from WTF measurements before and after implementation are given in Table 2. The magnitude of reduction was calculated based on the principle of calculating a relative change in the magnitude.

A diagram of change in the average working time factor of equipment is shown in Fig. 10.

In addition, we established a decrease in the time to enter the required temperature mode on average by 3.7 %. The dynamics of entering a temperature mode are shown in Fig. 11.

The dynamics of change in the time to enter a mode are given in Table 3.

Table 2

Dynamics of change in WTF before and after implementation

Period	WTF of absorption water-ammonia refrigeration unit the type of an island freezer			WTF of a single-stage ammonia refrigeration unit		
	before	after	decrease, %	before	after	decrease, %
January	0.59	0.58	1.69	0.42	0.4	4.76
February	0.57	0.56	1.75	0.49	0.48	2.04
March	0.63	0.62	1.59	0.55	0.53	3.64
April	0.71	0.7	1.41	0.62	0.6	3.23
May	0.76	0.755	0.66	0.68	0.67	1.47
June	0.77	0.765	0.65	0.77	0.75	2.60
July	0.82	0.815	0.61	0.79	0.77	2.53
August	0.85	0.845	0.59	0.83	0.8	3.61
September	0.87	0.865	0.57	0.73	0.7	4.11
October	0.69	0.68	1.45	0.6	0.56	6.67
November	0.62	0.61	1.61	0.53	0.5	5.66
December	0.6	0.585	2.50	0.46	0.42	8.70
Mean annual decrease in WTF, %	1.26			4.8		
Average decrease on WTF, %				2.67		

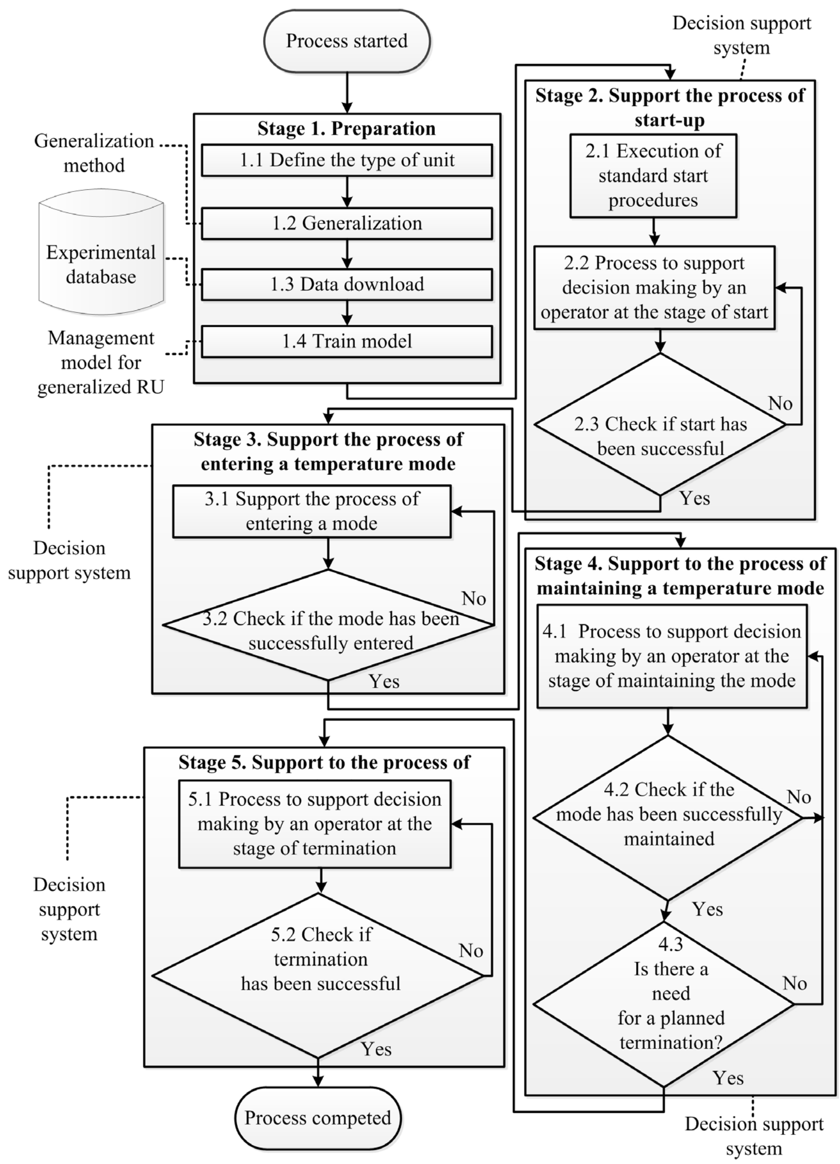

Fig. 8. Structural diagram for the information technology to support decision-making when managing refrigeration units

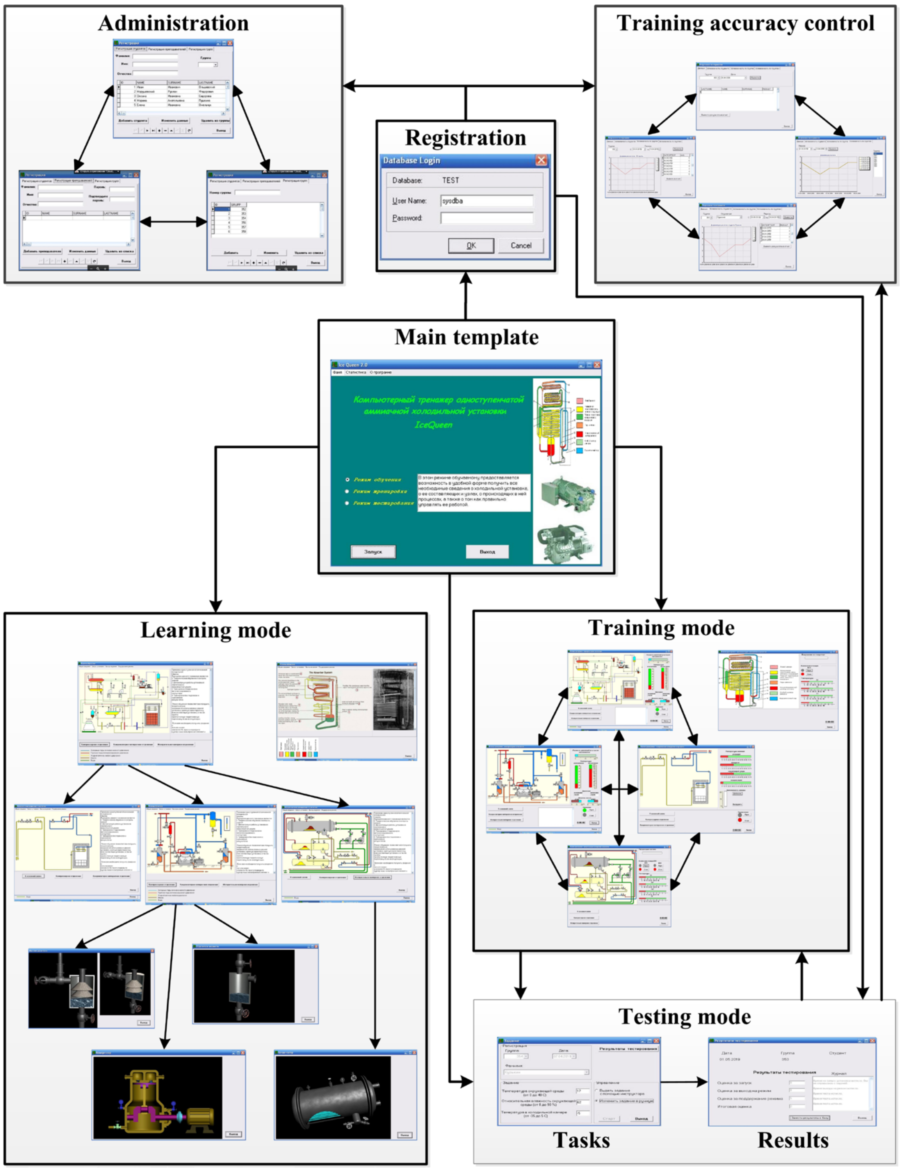

Fig. 9. Functional diagram of the computer simulator IceQueen

Table 3

The dynamics of change in the time required by a unit to enter a mode before and after implementation

Period	Time required by an absorption water-ammonia refrigeration unit the type of an island freezer to enter a mode			Time required by a single-stage ammonia refrigeration unit to enter a mode		
	before	after	decrease, %	before	after	decrease, %
January	10	9.6	4.00	13.5	12.9	4.44
February	9	8.65	3.89	14.4	13.7	4.86
March	11	10.7	2.73	15.7	15.2	3.18
April	13	12.6	3.08	16.6	16.1	3.01
May	15	14.5	3.33	18.1	17.5	3.31
June	21	20.2	3.81	19	18.5	2.63
July	23	22.2	3.48	19.4	18.8	3.09
August	23.5	22.6	3.83	20.1	19.5	2.99
September	23.3	22.2	4.72	19.7	19.1	3.05
October	15	14.4	4.00	17	16.3	4.12
November	13	12.5	3.85	15.6	14.8	5.13
December	12	11.5	4.17	14.8	14.1	4.73
Mean annual decrease in time, %			3.74			3.71
Average time decrease, %						3.73

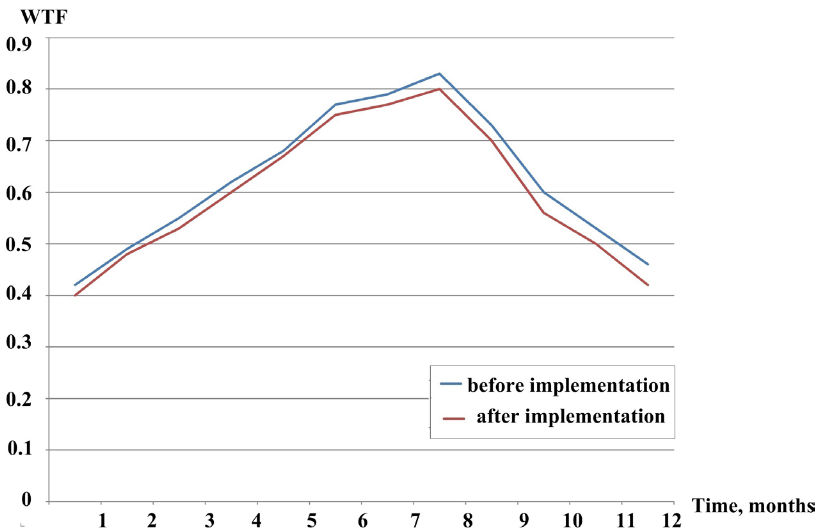

Fig. 10. Diagram of change in the average working time factor of equipment

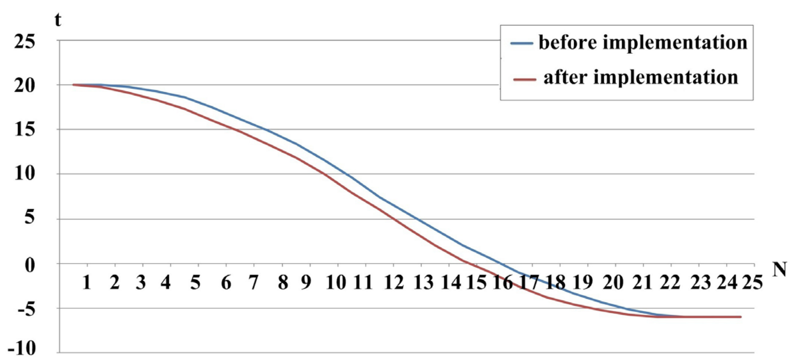

Fig. 11. Dynamics of entering a temperature mode: t – temperature, N – number of measurements

The speed and quality by a refrigeration unit to enter an appropriate temperature mode defines successful execution of global tasks that should be performed by a refrigeration unit in line with its purpose. This indicator has for a long time been treated as subjective, because there were no methods to improve efficiency of the equipment. At present, the speed required to enter a mode, as well as quality and safety of maintaining it, have become the objective indicator for consumer that is similar to a possibility to implement the mode and the size of capital investments. Therefore, optimization of any refrigeration unit can be expressed by unspent kilowatts of energy, which, in turn, have quite a specific cost.

6. Discussion of results of studying the models and methods underlying the new information technology

The scientific result from improving the method for generalizing a refrigeration unit implies the development of a generalized structural-functional scheme that, in contrast to existing, makes it possible, depending on the operational principles of various elements in refrigeration equipment, to consider, from unified systemic positions, possible configurations of actual refrigeration systems and complexes. Reducing an arbitrary unit to the form shown in Fig. 1 has become possible by using a concordance table (Table 1).

The improvement of the generalized model of the refrigeration equipment configuration is based on analysis, classification, and selection of typical elements in terms of execution of functions in the management scheme. That has made it possible to obtain a systematized description of basic structural elements of refrigerating machines that could be implemented based on different principles of operation. Those elements that do not directly affect the quality of management of a refrigeration system are excluded from the scheme of the system. Owing to this assumption, we have achieved a high level of unification. Reliability of the result obtained is explained by the correct use of stages in systems analysis in accordance with the principle of structural and functional concordance.

Based on the improved model of the generalized refrigeration unit, we have proposed the improved structure of a decision support process that makes it possible to automate the process of control action development by an operator. The improved scheme of the system to support decision making by an operator (Fig. 2) contains a unit that forms a reference control action, obtained based on the neuro-fuzzy training on data corresponding to the respective type of a refrigeration unit. The provided results from the verification of implementing such an approach, as well as improvements in performance, explain the correctness and appropriateness of the proposed scheme for intelligent support of decision making.

In the equipment of an industrial sample each element is a separate node whose operation could be described both by conventional modelling methods and by the proposed methods of neuro-fuzzy simulation. Application of the advanced neuro-fuzzy management model has made it possible to narrow the so-called boundaries of system distortion. This makes it possible to narrow down the difference between direct and reverse triggering of controlling elements, to improve smoothness of characteristics, which is confirmed by the above diagram of entering a mode (Fig. 8). In compact devices for commercial and household purposes the functionality and the purpose of elements could be combined. This to some extent complicates the use of the proposed model, but does not deny its usefulness given the confirmation of universality of the approach. When describing an industrial unit, several assumptions were accepted. All those elements that do not directly affect the refrigeration system operation and are used exclusively for auxiliary purposes were excluded from the scheme of the system. Automation of such elements' operation either is not implied or effectively resolved under a "manual" mode. Analysis of such elements is not interesting in terms of overall energy savings in the operation of refrigeration units.

The main scientific result of the current study is the information technology obtained, which is the result from improving models and methods related to managing industrial refrigeration units of different configurations (Fig. 8).

Our study allows us to assume a possibility to apply the technology described here when managing a refrigeration unit of arbitrary configuration. However, at present, there are confirmed data on the effectiveness of its application for several types of refrigerating plants. The developed information technology was verified at an ammonia single-stage industrial refrigeration unit at a meatpacking enterprise and at an absorption refrigerating machine for commercial and household purposes. The results from practical approbation of the introduction of the information technology, reported in chapter 5, are represented by factors that characterize energy savings in the general sense, namely, a working time factor (WTF) and the speed to enter a mode. The first case implies the ratio of operation time to downtime under a steady mode. The second case implies the time required to enter a steady mode. These two parameters depend on a large number of factors, among which there are no subjective ones. Even such a parameter as the ratio of the required cooling capacity to the actual capacity of equipment must not be ignored. However, as shown by Table 2, 3, the introduction of the proposed technology produced comparable results on two different systems.

When assessing the overall economic indicators, on has to operate the mean and relative magnitudes, giving them precedence over absolute. This is due to the fact that the considered energy systems operate under volatile environmental conditions that change. In addition, in winter ambient temperature is maximally close to the parameters for the system's configuration. At the same time, WTF and the time required to enter a mode could, for example, accept a null value. The merit of the applied data and observations is the long-term monitoring of their dynamics and the possibilities to derive general averaged economic indicators.

Based on tests (Tables 2, 3), WTF of the absorption machine was reduced by 1.3 %, WTF of the vapor-compression refrigeration machine was reduced by 4.8 % on average WTF was reduced by 2.7 %, the time-to-mode of the absorption machine was decreased by 3.74 %, the time-to-mode of the vapor-compression machine was decreased by 3.71 % on average the time-to-mode was reduced by 3.7 %. The results obtained could be expected. After all, the driving force in a vapor-compression unit is the pressure difference generated by a compressor. The driving force in the absorption machine is the difference in the density of weak and saturated water-ammoniac solutions at the input-output from a generating node. A difference in pressure is a more effective driving force and it is generally known that vapor-compression machines, owing to this, are more efficient. The main shortcoming of absorption machines, both for industrial and household purposes, is their inertiality. This explains a big difference between the results in reducing the WTF of absorption and vapor-compression machines. The results for reducing the time required to enter a steady mode were comparable in both cases because both types of systems employed the phase conversion of liquid ammonia into vapor as a means to obtain cold.

Unified character of the model underlying the information technology makes it possible to use it both when managing actual industrial refrigeration units and for training, for instance, during computer simulators (Fig. 9).

All the above indicates ways to resolve a task on improving the decision support systems when managing various types of refrigeration units by developing an information technology.

The drawbacks of the current study are due to the fact that at present there are confirmed data on effectiveness of using the developed information technology only for several types of refrigerating plants. Therefore, we consider it necessary to extend the experimental verification of the proposed approach to supporting decision-making at vapor-ejection and gas refrigeration machines. In addition, further improvement of the model is implied, as well as experiments, with the use of other types of neural networks in order to reduce error in training neural networks. Furthermore, we believe that one of the promising directions to advance the current study is to take into consideration the results from practical implementation when improving the interface part of the computer simulator IceQueen.

7. Conclusions

1. We have improved the method that makes it possible to reduce a refrigeration unit of any type and configuration to the general unified form, by conducting the generalization that implies analyzing the number and purpose of elements at individual units and reducing these elements to 4 predefined units. This makes it possible to consequently execute control using a unified model to support decision-making and to automate the process of its management.

2. We have improved a decision support system that enables correction of managing influences from an operator in compliance with the recommended control influences to optimize the decision-making process by a person who manages refrigerating equipment. The improvement implying the presence of a unit to form a reference control action based on neuro-fuzzy training on data corresponding to the type of a unit of refrigeration equipment makes it possible to manage various units in contrast to similar systems. Application of such a system has a positive effect on the speed of decision-making by an operator, which is confirmed by a decrease in the time required for a unit to enter a mode by 3.7 % as a result of our tests.

3. We have improved the model that ensures the formation of recommended managing influences by optimizing the quantity and quality of input and output parameters. The application of neuro-fuzzy simulation resolved the issue related to incompleteness and controversy within the model. The improvement makes it possible to apply the model for refrigerating units of any type and configuration. We have tested the model at vapor-compression and absorption refrigeration machines. Comparison of experimental data to the results from simulation at the stage of testing the model has revealed the values of errors in the range of 1.78~1.89, indicating the relevance of the model to practical requests.

4. A scheme of the structure of the new information technology to support decision-making when managing refrigeration units has been constructed, based on the above specified methods and models. Introduction of the information technology has led to the improvement in the equipment working time factor by 2.7 % on average and to a decrease in the time required for a unit to enter the required temperature level by 3.7 %.

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