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INFORMATION TECHNOLOGIES FOR THE SYNTHESIS OF RULE DATABASES OF AN INTELLIGENT LIGHTING CONTROL SYSTEM

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ABSTRACT

The results on the development and research of information technology (IT) for the synthesis and optimization of effective rule databases (RDB) with an optimal set of consequents and an optimal number of rules for fuzzy systems of the Mamdani type are presented. The study of the information model of the structure of the intelligent lighting control system based on fuzzy logic is carried out. RDB study for Smart lighting system was carried out. The possibility of minimizing the number of rules for the Smart lighting system, their optimization is shown, which, as a result, makes it possible to significantly simplify the further hardware and software implementation of such a system for various customers.

Keywords: *Information Technology, Smart Lighting, Fuzzy Logic*

1. INTRODUCTION

Intelligent computer systems (ICS), used in lighting control tasks and based on the theory of fuzzy logic (FL), fuzzy sets (FS), as well as soft computing, have recently been widely implemented at various Smart City facilities, starting with smart houses and ending with industrial production. The solutions currently used in smart lighting systems make it possible to quite effectively generalize heterogeneous information coming from sensors, formalize adoption mechanisms for controlling not only lighting, but also other Smart functions, as well as form linguistic models of lighting complex objects and processes. In many works in the field of Smart lighting, it has been shown that in such systems it is most advisable to use the mathematical apparatus of the FL when creating intelligent lighting control systems (ILCS), especially for tasks where objects operate under conditions of incomplete information and uncertainty.

For the effective use of fuzzy control systems (hereinafter - FCS) in solutions related to Smart lighting, at the stage of their development, it is necessary to successfully solve the following tasks of structural-parametric synthesis:

1) to determine the number of linguistic terms (hereinafter - LT) of input and output variables, as well as types and parameters of their membership functions (hereinafter – MF);

2) to synthesize FCS rule bases consisting of a set of antecedents and consequents;

3) to determine the types of aggregation, activation and accumulation procedures, as well as the defuzzification method;

4) to determine additional parameters (for example, normalizing factors for input and output variables).

2. LITERATURE REVIEW

Analysis of recent studies and publications shows that in many cases the above problems of structural and parametric synthesis of FCS are solved with the help of expert knowledge, assessments and recommendations. At the same time, as it was shown in [1], subjective factors have a significant impact on the FCS development processes, including for Smart lighting tasks. In the conditions of an insufficient amount of initial information and knowledge of experts regarding complex lighting objects (for example, smart street lighting, large industrial premises, large halls, sports facilities, etc.), as well as when making erroneous design decisions, the effectiveness of FCS Smart lighting can decrease significantly. In addition, it is possible that the functioning of such systems will be carried out with underestimated, in terms of potential, indicators.

In order to improve the efficiency of the functioning of the FCS Smart lighting, as well as to reduce the negative influence of subjective factors on the process of their design, researchers from many countries of the world develop and implement methods, algorithms and information technology (IT) for the synthesis of FCS [2]. Note that in order to solve this class of problems, various optimization procedures are mainly used [1–3]. For example, algorithms for structural optimization of FCS are often used on the basis of the optimal choice of MF types for LT, methods of defasification, reduction and interpolation of RDB. The results of such studies are described in [4, 5]. In [6], synthesis methods are considered, including procedures for the parametric optimization of the MF of FCS linguistic terms of the Mamdani type. In [7], the influence on the efficiency of the FCS of the weight coefficients for the consequent rules of the systems of the Takagi-Sugeno type is considered. As for the synthesis of highly efficient RDB with an optimal set of consequents and an optimal number of rules for Mamdani-type FCS with an insufficient amount of initial information (under conditions of a high degree of information uncertainty), this problem remains the subject of scientific research.

Thus, taking into account the above, an urgent task is the task associated with the development and research of IT for the synthesis and optimization of highly efficient rule databases with an optimal set of consequents and an optimal number of rules for the FCS Smart lighting (Mamdani type) in conditions of incomplete initial information about the lighting object.

The analysis of previous studies has shown that, despite a fairly large number of works in this subject area, the problems related to the development of smart lighting systems based on fuzzy logic for complex lighting objects are still relevant. For such objects, the adoption of erroneous design decisions reduces the effectiveness of fuzzy lighting control systems. The latter circumstance necessitated additional studies, the results of which are presented in this work.

3. METHODS AND MODELS

A generalized ILCS of the Mamdani type formalizes the relationship between the input and output variable based on a nonlinear dependence ϕ as follows [8]:

$$y = \phi(X), \quad X = (x_1, \ldots, x_n), \qquad (1)$$

where $X -$ vector of input variables $x_1, \ldots, x_n$; $y -$ initial variable of FS.

To implement the dependence (1) of the ILCS at the stage of fuzzification, the degree of membership of the numerical values of the input variables to the corresponding fuzzy input linguistic terms is estimated. After that, in the process of fuzzy logical inference, sequential operations of aggregation, activation and accumulation are performed using data from the rule database (hereinafter -RDB). RDB also includes a set of rules. This set consists of the corresponding antecedents (conditions) and consequents (inferences). The result of defuzzification will be the transformation of the consolidated fuzzy inference (resulting fuzzy set) into a clear numerical signal of the original variable for the ILCS.

When synthesizing a fuzzy ILCS, at the initial stage, a vector of input variables X and an output variable y are selected. Next, you need to choose the number of linguistic terms (LT) φ_i for each *j*-input variable of the vector X. It is also necessary to choose the number of LT ν for the output variable of the fuzzy ILCS.

At this stage, the types and parameters of the LT membership functions are also selected. Such a choice is realized for each variable of the ILCS, both input and output.

The total number of rules of the ILCS, built on the FL (rul), RDB of FCS lighting is determined by the number of all possible combinations of the LT of the input variables of the FS. According to [8], the total number of rules can be determined as follows:

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$$rul = \prod_{i=1}^{it} \varphi_i. \quad (2)$$

Then, each r-th rule of the RDB for the ILCS will represent a linguistic statement of the following form:

$$IF\ "x_1 = lt_1"\ \&\ "x_2 = lt_2"\ \&. \\ ..\&\ "x_i = lt_i" ... \& ... "x_n = lt_n" \\ THEN\ "y = lt_y", \quad (3)$$

Where $lt_1, lt_2, ..., lt_i, ..., lt_y$ – corresponding LT of input and output variables for the ILCS; it – number of iterations.

The antecedents of the rules are various combinations of LT of input variables of the FCS lighting. The consequent LT_r of each RDB rule is selected from the set of all possible consequents of the LT rules $\{LT^1, ..., LT^v\}$, i.e. $r = 1,2,...,rul.$

Therefore, it is true:

$$LT_r \in \{LT^1, ..., LT^v\}. \quad (4)$$

The vector of RDB consequents (V) can be formed in various ways. However, the solution of the problem of the synthesis and optimization of consequencies should be reduced to finding the optimal vector of consequents (V_{opt}) from the set of all possible alternative variants that provide optimal quality indicators for the lighting control fuzzy system.

The vector of consequents (V_κ) for the $k-$th alternative RDB variant in general form can be represented as follows [9]:

$$V_\kappa = \{LT_{k1}, LT_{k2}, ..., LT_{krul}\}, \\ LT_{kr} \in \{LT^1, ..., LT^v\}, k \in \{1,2,..., v^{rul}\}, \quad (5)$$

where v^{rul} – the number of all possible variants of the vector (V). This number is calculated as the number of LT for a variable v raised to the degree of the total number of RDB rules (rul).

Consequently, the task of creating a RDB with an optimal set of consequents is reduced to finding such a vector of consequents $(V_{opt} = V_k)$, at which the value of the objective function of the FS for lighting control will be optimal.

At the design stage of the ILCS, this task is assigned to the experts – developers. That is, the successful solution of the problem is directly related to the qualification of the expert. However, if the qualification of the expert or the amount of his knowledge is insufficient, it may be difficult to draw up a RDB. For example, if the value of the objective function F is not optimal for the vector V of RDB consequents formed by experts, then in order to achieve the optimal value F_{opt}, it will be necessary to carry out subsequent parametric optimization of the lighting control FS.

As for the creation of a RDB with an optimal number of rules $rul_{opt}(rul_{opt} < rul_{full})$, then such a RDB is understood as a base containing only those rules that have a significant impact on the functioning of the ILCS based on FL.

In order to identify and exclude rules from the base that do not affect or insignificantly affect the process of functioning of the ILCS on the FL, specialized methods and technologies for reducing the RDB can be used [8, 9]. However, note that these methods and technologies for reducing RDB are used after the synthesis of a complete RDB and require additional calculations, which are not always justified for budget Smart lighting projects.

The IT developed in the article helps to carry out the synthesis and optimization of highly efficient RDB for the ILCS with an optimal set of consequents (V_{opt}) and an optimal number of rules (rul_{opt}) under which the value of the objective function F of Smart lighting control processes will be optimal $(F = F_{opt})$.

The formation of the optimal vector of RDB consequents (V_{opt}) is carried out using iterative search based on a sequential search of the consequents of each RDB.

Also, in the process of searching for a vector (V_{opt}), the search for rules is carried out that do not affect the process of functioning of the ILCS. These rules are excluded from the RDB after finding the optimal vector of consequents (V_{opt}).

The proposed IT consists of the following sequential stages, taking into account the recommendations of works [9–11].

Stage 1. Initialization.

At the first stage, a preliminary synthesis of the structure of the complete RDB $(rul = rul_{full})$ is performed. This operation is performed on the basis of the selected input variables (X). As a result, a set of possible consequents for each rule (rul_{full}) is determined on the basis of the pre-selected (v) variable (y) of LT.

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The antecedents of the rules are formed on the basis of all possible combinations of the LT input variables. The initial number of full RDB rules (rul_{full}) is calculated according to dependence (2).

The initial vector of consequents (V_0), in turn, is randomly generated and set in the RDB of FS. In addition, at this stage, the type of objective function (F) is selected to assess the effectiveness of the ILCS, designed on the basis of FL. Also, the optimal value of the objective function (F_{opt}) is selected, for example, the color level of a certain spectrum, and the maximum number of iterations in the implementation of $\mathrm{IT} - IT_{\max}$.

Stage 2. Transition to the 1st rule of the ILCS RDB on FL.

At the second stage, the transition to the 1st RDB rule is performed. This transition allows to start iterative procedures for finding the optimal vector of RDB consequents (V_{opt}).

Stage 3. Checklist Verification (*CheckV*).

The checklist contains all vectors of the RDB consequent (V), for which the objective function (F) has already been calculated in the process of implementing IT, as well as the corresponding values of the objective function.

The checklist and its verification at this stage is applied in order to avoid repeated calculations of the objective function (F) for the ILCS based on the FL with the same vector of RDB consequents (V).

Thus, it is at this stage you can get rid of unnecessary iterations. That is, the following expression is implemented: $m \cdot (rul_{full} - 1)$, where $m-$ the number of cycles of sequential iterative procedures for optimizing RDB rules from the first to (rul_{full}).

If the current vector of RDB consequents (V) is already entered in the *CheckV*, then the transition to stage 7 is performed. Otherwise, the transition to stage number 4 is performed.

Stage 4. Calculating the value of the objective function (F) with the current vector of RDB consequents (V).

At the fourth stage, the value of the objective function (F) is calculated for the ILCS based on the FL with the current vector of the RDB consequents (V). After that, the iteration counter is increased by 1.

Stage 5. Checking the completion of optimization of the vector of RDB consequents (V).

Optimization of the vector of RDB consequents (V) for the ILCS based on FL is considered complete if:

1) the optimal value of the objective function $(F \le F_{opt})$ is reached;

2) the maximum number of iterations has been performed $IT_{\max}$.

If such a check gave a positive result, then the transition to Stage 10 is performed. Otherwise, we proceed to Stage 6.

Stage 6. Recording a vector $(V(IT))$ and its objective function $(F(IT))$ in the *CheckV*.

At this stage, the current vector of RDB consequents $(V(IT))$ and the corresponding objective function value $(F(IT))$ are written into the checklist.

Stage 7. Checking the completion of the optimization process for the current *r*-th rule for the ILCS based on FL.

Optimization calculations for the current rule of the ILCS RDB based on FL are considered completed if the values of the objective function (F) for each consequent were calculated for the set of all LT v of possible consequencies for this rule.

If such a check gave a positive result, then go to step 8.

Otherwise, this rule sets the following consequent: $LT_r^{j+1}, j \in (1,2,\ldots,v)$ from a set of possible consequents. Then go to step 3.

Stage 8. Choosing the best consequent.

At the eighth stage, the consequent is selected, for which the value of the objective function (F) of the ILCS based on FL is the smallest among those obtained during the optimization calculations for the current *r*-th rule, and it is set in this rule.

Stage 9. Checking the number of the current rule of the ILCS RDB based on the FL.

At the ninth stage, the number of the current RDB rule is checked. If all RDB rules $(r = rul)$ are optimized, then the transition to stage 2 is performed.

Otherwise, proceed to the next rule and then go to stage 3.

Stage 10. Identification of rules that do not affect the process of functioning of the ILCS based on FL.

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At the tenth stage, the rules are identified, during the optimization of which the value of the objective function (F) for the ILCS did not change when all possible consequents were changed one after the other.

Since sequential iterative optimization procedures for RDB rules can be carried out (m) once (cycle) until the optimal vector of RDB consequents (V_{opt}) is found, at which $(F \le F_{opt})$, then the definition of insignificant (unnecessary) rules is carried out only on the last round of optimization.

Stage 11. The procedure for excluding rules that do not affect the process of ILCS functioning.

At this stage, the identified unnecessary rules (which do not affect the process of ILCS functioning of) are excluded from the RDB.

As a result, the number of RDB rules will be reduced $(rul < rul_{full})$.

Stage 12. Completion of the process of synthesis and optimization of the RDB for the ILCS.

After the penultimate stage, you can perform additional parametric optimization of the fuzzy lighting control system and its software and hardware implementation.

At the same time, the hardware and software implementation will be simplified due to the reduced number of RDB rules $(rul < rul_{full})$.

The Fig. 1 presents the block diagram of the synthesis and optimization algorithm of the rule database for the ILCS. Note that Fig. 1 contain a block diagram of IT for the synthesis and optimization of RDB with an optimal set of consequents and an optimal number of rules for Mamdani-type for FS under conditions of incomplete initial information.

When applying the given IT, the maximum number of iterations $(IT_{\max})$ can be found as follows:

$$IT_{\max} = m \cdot \lfloor rul_{full} \cdot v - (rul_{full} - 1) \rfloor. \quad (6)$$

The number of cycles m is easy enough to select experimentally, for example, in the course of computational experiments in the MATLAB environment.

In the presence of an already developed RDB with a certain vector of consequents (V) based on expert knowledge and assessments, the proposed information technology can be used to further optimize this RDB in order to increase the efficiency of the system on the FL and simplify its software and hardware implementation by reducing the number of rules in the RDB.

At the same time, at the first stage of IT application, the initial vector of consequents (V_0) is determined on the basis of the experts knowledge and is installed in the RDB of the fuzzy system, in our case for the ILCS.

All other stages of this IT are performed in the same way as in the absence of knowledge and expert advice. However, if there is prior knowledge of experts (or the so-called initial hypothesis) with respect to the vector of consequent (V_0), iterative RDB optimization procedures can be performed only once (i.e. $m = 1$). This will significantly reduce the total number of iterations $(IT_{\max})$.

Informational description of the structure of the design object – "Intelligent lighting control system (ILCS)" should consist of two parts.

The first part contains a description of the lighting object itself, for solving a specific technical problem. For example, living quarters (rooms of an apartment, rooms of a house), a cinema, a shopping center, a conference room, a greenhouse, etc.

The second contains a description of the design process of the ILCS.

The first part formalizes a typical block-hierarchical representation of systems. We use this part of the information model for tasks in which the mutual subordination of the elements used and the assignment of additional descriptions to them is used.

The minimum set of data required to describe the components of the ILCS structure can be represented as follows:

$$OS = \left\langle \begin{matrix} idST, idP, ObSTN, \\ idPOS, Spec, Com, FN \end{matrix} \right\rangle, \quad (7)$$

where $OS -$ description of the designed object – ILCS; $idST -$ identifier of the ILCS description element; $idP -$ identifier of the ILCS auxiliary component; $ObSTN -$ description element of the designed ILCS; $idPOS -$ the identifier of a specific design object of an ILCS component, for example, for ILS; $Spec -$ design item specification; $Com -$ a state describing the belonging of a specific description element as part of the ILCS elements for a higher level of the hierarchy (for example, software for a dimmer); $FN -$ a file containing additional structured and unstructured data with a description of the specific properties of the ILCS.

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The tuple (7) is the main form of the information model of the object structure – ILCS. Since it is an example of using the object-attribute formalism, we will consider the solution of the local problem of constructing effective RDB on a given interval for the functioning and operation of the ILE in the Smart House network.

Initial conditions of the task:

Let:

the objective function (OF) is set, which characterizes the minimum allowable illumination level [12].

It is required to compose an algorithm for the ILCS based on FL.

Certain requirements are imposed on the implementation of each of the ILCS modes.

All these requirements are denoted by

$$RE = \{RE_1,...,RE_i,...,RE_g\}, \qquad (8)$$

where $g-$ the total number of requirements depending on the number of modes of operation of the ILCS. Requirements (or criteria) are determined either by the customer (if the ILCS is developed as an individual solution) or by the designer. Here RE_i- is a requirement that the designer defines.

The requirement or criteria RE_i has the following meanings (content, characteristics): the level of illumination (or the power of the ILS).

There are other requirements as well. It is fashionable to refer to such additional requirements:

Reliability of work (not less than E);

power capacity not less than P;

protection against signal transmission for ILE control;

etc.

There are also a number of requirements for the quality of performance of the ILCS work operations:

$$Q = \{Q_1,..., Q_h\}, \qquad (9)$$

where $h-$ the number of requirements and criteria for performance (support of the performance process and the result of performing work operations for the ILCS). The value h (number of requirements and criteria) is determined by the task or specific task of lighting control. Q_i – requirements for the implementation of the ILCS working operations:

response speed;

minimization of costs and expenses;

etc.

Objective function is a criterion that must be minimized or maximized, depending on the user's requirements. For example, when working at a desk, the illumination should be maximum, and the Smart lighting system adjusts itself to the person. On the contrary, when watching TV or the level of illumination should automatically decrease, thereby creating comfort for the organs of vision. One of the design parameters of the ILCS for Smart lighting is the number of ILE (*N*) in the area of Smart lighting, which is determined as follows:

$$N = \frac{E \cdot S \cdot K_{st} \cdot z}{\Phi \cdot \eta}, \qquad (10)$$

where $E-$ standard indicator of illumination for comfortable work or rest of a person; $S-$ area of the illumination zone for a specific ILE; $K_{st}, z-$ power reserve coefficients of Smart lighting ILE and uneven lighting, respectively; $\Phi-$ the intensity of the luminous flux from a separate ILE in the area of operation of Smart lighting, lm; $\eta-$ coefficient taking into account the design features of the room (height, colors in the room, etc.).

As for the specific type of objective function, then a lot depends on the specific structural elements of Smart lighting and the type of premises (house, apartment, cinema, shopping center, warehouse, etc.). For example, for residential premises in which "smart" LED lamps are installed for the Smart lighting system, the objective function characterizing the spectral distribution density of the LED lamps ($f(RGB)$) can be written as follows [13]:

$$f(RGB) = wb \cdot B + wg \cdot G + wr \cdot R,$$

where $wb, wg, wr-$ emission weight coefficients for the spectra of blue, green and red colors ((R,G,B)) for ILE type LED lamps.

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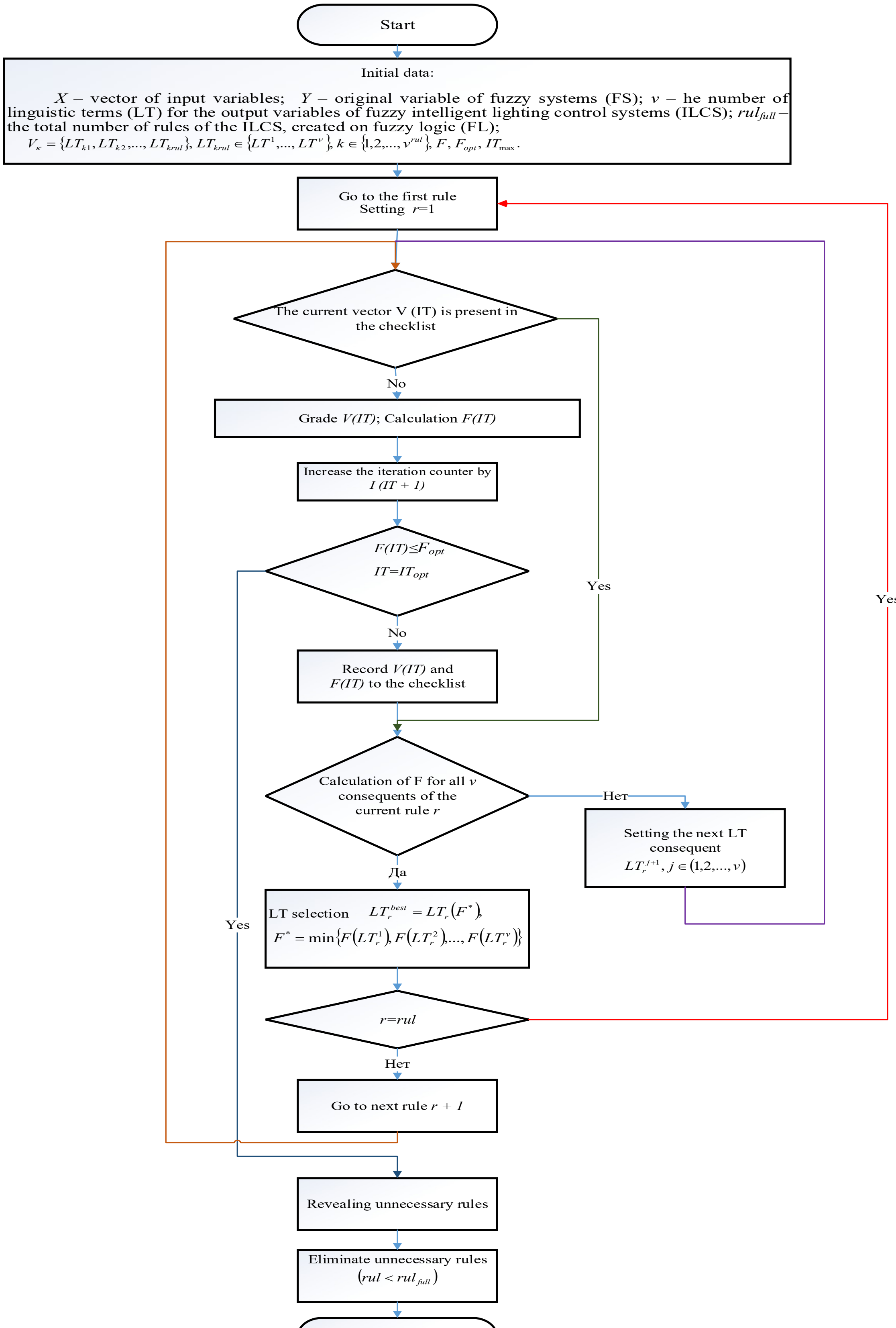

Figure 1 : Block diagram for the synthesis and optimization of the rule database for the ILCS

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Then the ILCS for Smart lighting should control the lighting based on the task of implementing the function of the form [13]:

$$\frac{|f(RGB) - f(D65)|}{f(D65)} \to \min,$$

$f(D65)-$ spectral distribution of luminous flux from LED light source D65.

Taking into account the works [14, 15], we will use the fuzzy modeling apparatus for the procedure for the synthesis of the RDB ILCS in order to construct the Mamdani FIS.

If we talk about the rules for RDB ILCS, then it is possible, in general, to accept the following parameters for fuzzy control of Smart lighting:

Power of the luminaire equipped with an LED light source and the corresponding luminous flux;

ILCS cost;

IMIS functionality in the context of the choice of the number of lighting modes.

Step 1: Define the input linguistic variables and their ranges.

There are three color temperature ranges for work or rest when using the ILE with LED lamps. The ranges depend on the temperature of the LED light source, which is measured in Kelvin (K), see table 1.

Table 1 : Color temperature in the operating area of the ILE with LED light source (K) (Parameter – Lighting color temperature or LCT)

Linguistic range	Upper bound	Lower bound
Warm white light	3800	2300
Natural white light	4800	3700
Cold white light	6700	4700

We will accept three power ranges of a luminaire equipped with an LED light source and having a corresponding luminous flux (Lm / W), see table 2.

Table 2 : Luminaire power / corresponding luminous flux (lm / W)

Linguistic range	Upper bound	Lower bound
High	30/2500	21/2100
Medium	22/2200	13/1300
Low	14/1400	10/900

There are three ranges for the ILCS cost, see table 3.

Table 3 : The cost of Smart lighting or ILCS (for example, in USD)

Linguistic range	Upper bound	Lower bound
High	50	25
Medium	27	8
Low	9	5

There are three ranges for regulating the color temperature in the area of operation of the ILE with LED light source (s) - the functionality of the ILCS in the context of the choice of lighting modes (by the number of selection ranges), see table 4.

If we complicate the ILCS, for example, by going along the path of increasing the number of power switching modes and the corresponding luminous flux, this will not only lead to an increase in the ILCS cost, but also reduce the environmental performance of the Smart lighting system, since at higher temperatures of LED light sources, the burden on the environment increases.

Table 4 : ILCS functionality in the context of the choice of the number of lighting modes

Linguistic range	Upper bound	Lower bound
High	>15	7
Medium	8	3
Low	4	1

Step 2: Define linguistic output variables and their ranges.

In general, if we consider all possible output variables for the ILCS, then there may be several of them, for example, the following:

electricity consumption (we strive to reduce);

operating costs (we strive to reduce);

service life of ILE (we strive to increase);

the economic effect, which is associated with the possibilities of automation of management and the organization of accounting for electricity consumption in the ILCS system for Smart lighting (or the economic effect of the introduction of Smart lighting).

However, given that, ultimately, the last variable - the economic effect, which is associated with the possibilities of automation of management and the organization of accounting for electricity consumption in the ILCS system for Smart lighting, is complex. This output variable can integrate other output variables, including a decrease in electricity consumption, and a decrease in operating costs for lighting, and an increase in the service life of an ILE and a decrease in the frequency of replacing light sources, etc. we will assume that the variable is the economic effect of Smart lighting implementation is integral and covers all aspects of the process of using the LCS with the developed RDB. Based on the foregoing, when constructing RDB on an FL apparatus, we will assume that there is one output variable – the

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coefficient of economic efficiency of the ILCS for the Smart lighting system (or ECE), see table 5.

Table 5 : Coefficient of economic efficiency of ILCS for the Smart lighting system (ECE)

Linguistic range	Upper bound	Lower bound
Very high	0,75	1
High	0,50	0,76
Medium	0, 25	0,55
Low	0,15	0,30
very low	0	0, 25

Step 3: Determine a set of fuzzy membership functions for each input and output variable.

Gaussian MF (Exponential (Gaussian) Membership Function) is used due to the short notation and smoothness of the Gaussian function.

Each range of input and output variables defines a relationship with fuzzy sets, which have the same designation in the corresponding range.

Step 4: Using information technology, we will create a RDB that regulates the work of FIS (ILCS for Smart lighting).

There are four fuzzy input variables and three fuzzy sets for each fuzzy variable. The maximum possible number of rules in our rule base is $3^4 = 81$.

The RDB will contain "*If – Then*" rules, examples of which are below:

if the *LCT* is defined as "*Cool white light*", and the luminaire power / corresponding luminous flux is "*high*", and the cost of Smart lighting or ILCS is "*high*", and the functionality of the ILCS in the context of the selection of the number of lighting modes is "*low*", then ECE is "*very high*" ;

if the *LCT* is "*Warm white light*", and the luminaire power / corresponding luminous flux is "*high*", and the cost of Smart lighting or ILCS is "*medium*", and the functionality of the ILCS in the context of the choice of the number of lighting modes is "*low*", then ECE is "*very high*";

if the *LCT* is "*Warm white light*", and the luminaire power / corresponding luminous flux is "*high*", and the cost of Smart lighting or ILCS is "*medium*", and the functionality of the ILCS in the context of the choice of the number of lighting modes is "*low*", then ECE is "*very high*";

if the *LCT* is "*Natural white light*", and the luminaire power / corresponding luminous flux is "*high*", and the cost of Smart lighting or ILCS is "*low*", and the functionality of the ILCS in the context of the choice of the number of lighting modes is "*medium*", then ECE is *"low";*

etc.

4. COMPUTATIONAL EXPERIMENT

The proposed rules at this stage of the study were implemented in the MATLAB Fuzzy Logic Toolbox. This environment was chosen due to its availability and the presence of a special unit for working with a fuzzy logic apparatus - Fuzzy Logic Toolbox.

The above steps 1 through 4 are linked to steps 5 through 8.

Step 5: Fill in the input data.

Step 6: Apply the indirect method as it does not require additional memory allocation to return the result.

Step 7: We enter in the knowledge base a set of all the initial data necessary to study the influence of input factors on the efficiency of the ILCS.

Step 8: Process the data (deffuzify).

As a result at the output, we get a clear " ECE indicator" for each of the sets of input variables. This is convenient at the stage of researching promising designs of Smart lighting systems or ILCS.

After defuzzification, the resulting " ECE indicator" can be used to determine whether it is necessary to implement a particular design in the form of a hardware-software solution for Smart lighting systems or ILCS.

If an ECE indicator is $>0{,}85$, then such a design may be promising and it is worth considering its commercial use. Otherwise, if the ECE indicator is $<0{,}85$, you should not do this.

The modeling of the input and output parameters presented in tables (1–4) is performed in the Matlab environment.

Such imitation modeling made it possible to check the performance of the basic rules for various options for varying the values of the variables characteristic for the research and design stage of the development of Smart lighting systems or ILCS.

Figure 2 shows a general view of the Smart lighting system for the case of using only 4 input variables and one output value.

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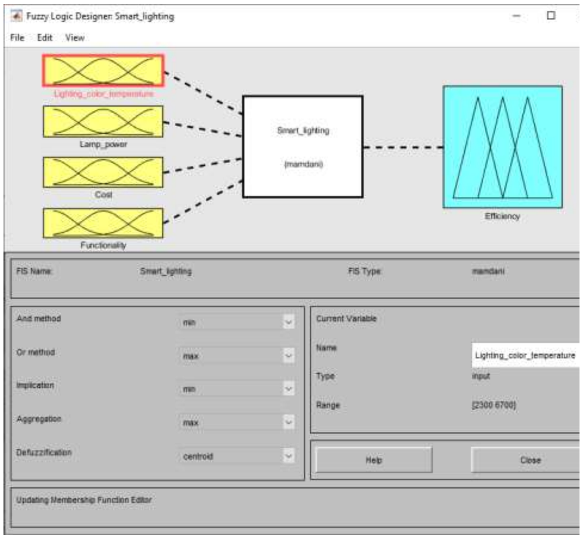

Figure 2 : General View Of The Smart Lighting System For 4 Input Variables And One Output Value

After the properties of the input variables are set in the rules window, you can create all the fuzzy rules for the Smart lighting system, see fig. 3.

And although the rule editor in Fuzzy Logic in MatLab software is quite functional, it does not always allow to directly optimize the RDB. This is especially noticeable with a large number of input variables and more than one output variable.

The rule entry fields located in the middle of the editor window provide the developer with the flexibility to compose rules. Moreover, you can use the models of fuzzy inference of Mamdani or Sugeno. Note that there is a possibility of a situation when some terms are not included in the rules. Then the value *none* is chosen for such terms. This additionally increases the total number of rules in the RDB.

The Fuzzy Logic rule editor of MatLab software allows at the design stage of the FCS to additionally use the operations of logical negation of some terms (by checking the checkbox with the *not* mark). This also increases the number of rules.

Note that many authors of fundamental works devoted to the theory of FL and FS, for example, the founder of the FL theory Lotfi Aleskerzade [16] and others [17] note that, based on the analysis of the properties of relatively simple operations, in many cases it makes sense to approximate their results with using a triangular membership function. This makes interpretation much easier. On Figures 4, the window displaying the operation of the FL rules using the vertical red line (indicated by line 1, see Fig. 4) can be used to move the values of logical variables to the left or to the right. For example, shifting line 1 on Figure 4 slightly to the right for input variables:

1) luminaire power / corresponding luminous flux;

2) Smart lighting or ILCS cost,

and to the left for a variable color temperature in the area of operation of the LED source and leaving in the middle position the variable functionality of the ILCS in the context of choosing the number of lighting modes, you can immediately notice that the value of the output variable – the coefficient of economic efficiency of Smart lighting, will be 0.437. And this immediately transfers the potential scheme of the Smart lighting system into the category of medium efficiency, which makes it commercially attractive and, accordingly, allows to move on to other stages of development, for example, calculating the cost price.

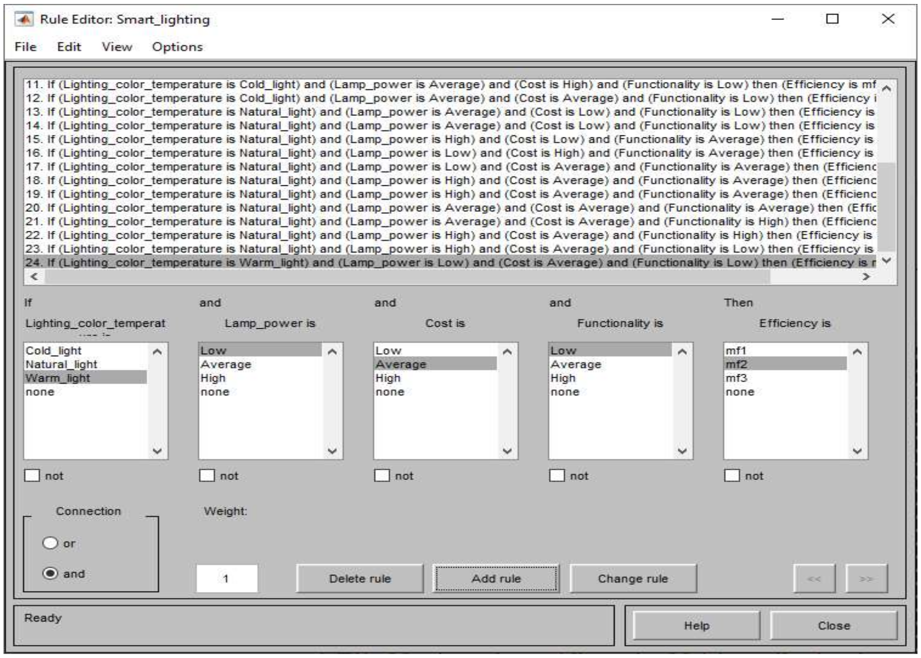

Figure 3 : Window of the rules editor in Fuzzy Logic software MatLab

It is obvious that the commercial attractiveness of the project will be primarily influenced by the cost of components for the Smart lighting system. And only when the cost of components is minimized it make sense to transfer the project to the hardware-software stage of implementation. Although it is possible to find examples of real systems [13], positioned as maximally ecological, when, at a high cost of components, their ecological indicators are at a high level by maximizing the use of energy-saving lighting modes, when the heat release into the environment is minimal.

Figure 4 : Window for viewing the work of Smart lighting rules

Also note that the task to maximize the environmental performance of the work can be immediately negotiated by the customer when drawing up the technical task. So many developers of Smart lighting systems for smart cities initially choose this approach, trying to implement Smart with minimal impact on the environment.

Similar studies were carried out when studying the influence on the coefficient of economic efficiency of Smart lighting from such variables as:

1) Smart lighting or ILCS cost;

2) luminaire power / corresponding luminous flux.

For such a pair of variables, the influence is not so unambiguous. So the maximum values of the coefficient of economic efficiency of Smart lighting can be obtained for the average values of the cost of components and average values of the lamp power / corresponding luminous flux.

Having prepared the parameters for solving the task of choosing the parameters of the FCS, we introduce the weight scale for each criterion, see Fig. 5.

It was accepted:

1 – FCS cannot be applied (0,0,0.25);

2 – it is possible to apply FCS for Smart lighting (0,0.25, 0.75);

3 – average level of FCS application for Smart lighting (0.25, 0.5, 0.75);

4 – should apply FCS and RDB for Smart lighting (0.5,0.75,1);

5 – it is necessary to apply FCS and RDB for Smart lighting (0.75,0.75,1)).

Let's introduce a five-level scale of linguistic terms to assess the level of correlation between a specific indicator of the state of Smart lighting and a specific criterion: 1 – "very low"; 2 – "low"; 3 – "medium"; 4 – "high"; 5 – "very high".

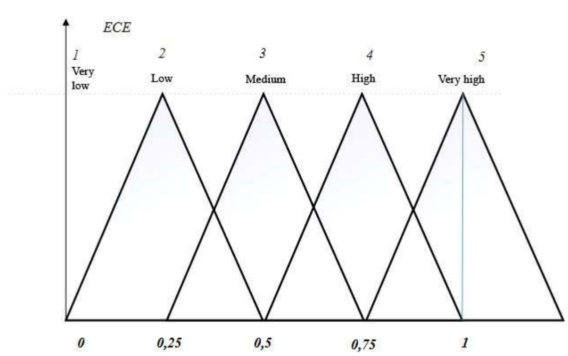

Figure 5 : Scale of assessments and membership functions of the corresponding linguistic terms

This allows to estimate the value of the ECE parameter level.

The next step is the formation of empirical weight coefficients B_1, B_2, B_3 and B_4, (for 4 input variables), which can take values, for example, in the range from 1 to 3. The range is selected expertly.

Note that a larger value of the coefficient means a greater weight of the specified parameter for the implementation of Smart lighting or ILCS [18–25].

The ECE determination procedure, depending on the specific technologies that can be implemented for Smart lighting or ILCS, may lead to changes in ECE indicators:

$$ECE = (q_1, q_2, q_3)_{mn}, \qquad (11)$$

$$q_{j_{mn}} = \sum_{i=1}^{4} \left(ECE_{i_{mn}} \times l_{ij_{mn}} \right), \quad (j = 1,2,3), \qquad (12)$$

where $q_1, q_2, q_3 -$ the lower level of the ECE generalized assessment, its main meaning and the upper level, respectively; $ECE_{imn} = (l_{i1}, l_{i2}, l_{i3}) -$ triangular fuzzy number, characterizing the indicator of the Smart lighting parameter or ILCS with $i-$th criterion. Moreover, the element itself is Smart lighting or ILCS with a serial number m and uses the $n-$th technology; $l_{i1}, l_{i2}, l_{i3} -$ the lower level of a linguistic variable, its main meaning and the upper level, in accordance with the format of triangular fuzzy numbers (Triangular Fuzzy Number).

Thus, based on the use of IT, the initial vector of consequents (V_0) was determined and installed in the RDB of a fuzzy lighting control system [20, 23, 25].

Note that if experts have prior knowledge of the consequent vector (V_0), iterative RDB optimization procedures for the Smart lighting system can be performed only once (i.e. $m = 1$). This will significantly reduce the total number of iterations $(IT_{\max})$.

The improved method provides the possibility of adapting the rules in the RDB and optimizing their number, depending on the various input parameters of the FCS Smart lighting.

5. CONCLUSIONS

The following results were obtained in the work:

presented the results on the development and research of IT for the synthesis and optimization

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of effective rule databases with an optimal set of consequents and an optimal number of rules for fuzzy systems of the Mamdani type;

the study of the information model of the structure of the object was carried out; an intelligent lighting control system based on fuzzy logic;

the study of RDB for the ILCS was carried out. The possibility of minimizing the number of rules for the Smart lighting system and their optimization is shown, which, as a result, makes it possible to significantly simplify the further hardware and software implementation of such a system for various customers;

there was shown that in the process of synthesis and optimization of RDB with an optimal set of consequents and an optimal number of rules for the ILCS, proposed in the work of IT, and the corresponding algorithms do not require significant computational costs, which is important for the design of RDB not only for the ILCS, but also for other different types of FCS, but also decision support systems;

the method of choosing rules for ILCS or Smart lighting has been improved based on the application of the theory of fuzzy sets. In the proposed method, it is possible to adapt the decision-making rules, depending on the various input parameters of the FCS Smart lighting.

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