ANALYSIS OF TECHNICAL INDICATORS OF EFFICIENCY AND QUALITY OF INTELLIGENT SYSTEMS

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ABSTRACT

The efficiency of intelligent systems refers to their ability to achieve set goals and perform tasks with high quality and efficiency. It is determined by the effectiveness of the system in the context of its functionality, productivity, accuracy, and speed of solving tasks. The efficiency of intelligent systems can be evaluated according to several criteria. For example, efficiency can be related to the time it takes to complete tasks, the amount of resources used, the quality of problem-solving, or the system's ability to adapt to changing conditions. Various indicators and metrics can be used to measure the performance of intelligent systems, such as response time, classification accuracy, data processing speed, use of resources (for example, memory or computing power), etc. The performance of intelligent systems is an important aspect of their development and application, as it determines their ability to achieve positive results and perform tasks with maximum productivity and quality.

Keywords: *Intelligent Systems, Multi-Agent Systems, Adaptive Systems, Efficiency Indicators*

1. INTRODUCTION

Intelligent systems are complex systems that use intelligent methods, algorithms and technologies to analyse, understand and solve complex tasks. They can show intellectual ability, self-organisation, learning and adaptation to change. The efficiency of intelligent systems is determined by their ability to achieve set goals and perform tasks with maximum productivity, accuracy and speed. Its evaluation is based on various factors: speed of information processing, level of accuracy in solving tasks, ability to learn and adapt, cooperation with other systems or users, use of resources and other requirements, depending on the specific application context.

Intelligent systems include various components that cooperate with each other to achieve common goals [1]. Some of the key components of intelligent systems include sensors, algorithms and models, knowledge bases, agents, interfaces. Sensors provide the collection of input data from the physical environment or from users. Algorithms and models are used to process and analyse data, make decisions, develop forecasts or create behavioural models [3, 7]. Knowledge bases contain information, rules, and expert knowledge that are used to understand tasks, solve problems, and make decisions. Agents can be autonomous entities that perform certain tasks and interact with other agents or external systems. Interfaces provide interaction between the system and users or other systems [1, 24].

Components and subsystems of intelligent systems are individual constituent parts that cooperate with each other to function and achieve system goals. They can have different functions, roles and interrelations. The main purpose of the components and subsystems of intelligent systems is to ensure the operation of the intelligent system as a whole and to ensure that its tasks are fulfilled [6, 11, 23]. These components interact with each other, exchanging information and cooperating to achieve desired results.

Components are the basic building blocks of an intelligent system; they can be physical objects or software modules. They can include elements like sensors, actuators, computing units, algorithms, knowledge bases, models, interfaces, etc. Each component has its own specific function and interacts with other components to achieve the common goals of the system.

Subsystems of intelligent systems are groups of interconnected components that work together to perform certain functions or subtasks of an intelligent system. These parts of the system can be more specialised and independent. For example, an intelligent system may include subsystems of an intelligent system for data processing, solving attern recognition tasks, decision-making, communication with the user, etc.

Components and subsystems of an intelligent system interact with each other and with the external environment, exchanging data, information and control, which allows the system to function and achieve its goals. The interaction and cooperation between the components and subsystems of an intelligent system is an important aspect of the development and optimisation of intelligent systems.

Due to the heterogeneity of intelligent systems, it is necessary to develop indicators that will be applied to various components of the system (regardless of their nature) to analyse and understand the effectiveness of the intelligent system.

The activity of the intelligent system and its subsystems is considered to be a communication activity within the framework of the approach that uses the communication theory [7, 24]. According to this approach, the interaction of system components is interpreted as a communication process where various elements interact by exchanging information and signals. The activity of an intelligent system and its subsystems may include the following steps: data/knowledge collection, during which the system collects input data/knowledge from various sources or from experts/users; knowledge/data processing, as the collected knowledge/data is analysed, processed and transformed according to the system's internal algorithms and rules; task solving (during this stage the system performs defined tasks using processed knowledge/data and developed models or algorithms); communication and interaction, where system components exchange information, signals, or commands to coordinate actions and cooperate with each other; conclusions and decisions, because based on the processed knowledge/data and results of tasks, the system can draw conclusions, make decisions or generate answers. In this approach, the activity of an intelligent system is considered is considered in terms of interaction and communication between components and subsystems of an intelligent system. The characteristics of this communication determine the technical efficiency of the intelligent system and are used to measure and evaluate its efficiency and quality [5, 7, 14].

2. LITERATURE REVIEW AND ANALYSIS

In the literature, various approaches to analyzing the technical indicators of efficiency and quality of intelligent systems can be found. Some researchers focus on measuring the accuracy and completeness of the system, which are key performance indicators [7, 9, 13]. Metrics such as precision, recall, specificity, and F-measure can be used for this purpose. Additionally, there are approaches used to measure the speed and efficiency of data processing by intelligent systems [30-33]. Furthermore, literature contains works dedicated to measuring the robustness to noise, reliability, and security of intelligent systems. These indicators are particularly important in the context of critical domains, such as medicine or autonomous transportation. Overall, the analysis of technical indicators of efficiency and quality of intelligent systems is based on the use of various metrics and measurement methods, which are determined according to the specific context and research objectives [5, 8, 10, 12, 17, 21, 26-34]. Literary sources provide insights into theoretical aspects, an overview of methodologies, and practical results, helping to establish evaluation standards and improve the quality of intelligent systems.

3. RESEARCH GOAL

The main goal of the research is to analyse the technical indicators of efficiency and quality of intelligent systems. The research aims to examine different approaches for measuring and evaluating the performance of intelligent systems, including metrics such as accuracy, completeness, data processing speed, and robustness to noise. Additionally, the research seeks to identify methodologies and metrics that are most suitable for meeting specific requirements and aligning with the application context of intelligent systems.

4. MODELS AND METHODS

To represent different subsystems of intelligent systems in the form of communication systems, it is necessary to describe the activity of each subsystem (because for each subsystem it is necessary to determine which actions it performs, what input and output data it processes, how it communicates with other subsystems and what interactions happen within it); to apply the principles of communication theory, where it is necessary to create dependencies between the subsystems of the intelligent system so that they can exchange information and interact with each other; to use models of communication systems (because for a better understanding and analysis of interactions between subsystems of an intelligent system, it is possible to use models of communication systems, such as data transfer models, agent interaction models or network communication models); to take into account the features of each subsystem of the intelligent system. Each subsystem of an intelligent system may have its own characteristics and requirements for communication [4, 20, 22, 24]. For example, message transfer protocols can be used for computing agents, control signals can be used for mechanical components, and interface interaction can be used for human operators. This work allows the presentation of various subsystems of the intelligent system in the form of communication systems and ensures their interaction and exchange of information within the limits of the intelligent system.

Fig. 1 shows a general view of an intelligent system, where the boundaries define all subsystems of the intelligent system involved in the performance of a task or process. Computing agents, mechanical components, applications, or even a human operator with a specific role can make up different subsystems of an intelligent system [5, 30-33].

Different types of subsystems of intelligent systems can differ significantly in their nature, structure and the role they play in the overall intelligent system. This complicates the task of designing and analysing the performance of an intelligent system, because each type of subsystem of an intelligent system uses its own models and principles [8, 20]. For example, computational agents, mechanical components, software applications, or even people with their unique characteristics and abilities can be the subsystems of an intelligent system. Each type of subsystem may have its own characteristics and requirements for operation, interaction, and performance measurement.

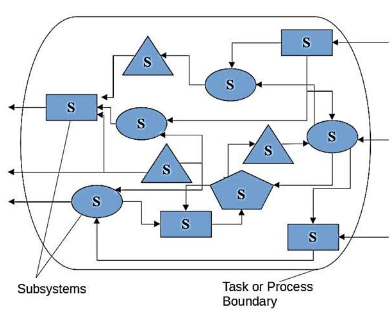

Figure 1. The general structure of the intelligent system. (The drawing was created using the vector graphics editor LibreOffice Draw)

Therefore, the task is to find a common approach to the analysis and modelling of different types of subsystems, which will allow us to describe their performance in a common language and framework [13, 22, 25, 32]. Considering the activity of subsystems as communication systems can be one of the possible ways of solving this task, which allows to generalise the aspects of communication and interaction regardless of the type of subsystem. Communication activity involves the exchange of information between a source (sender) and a destination (receiver) in order to convey a message. It includes transmission, reception, understanding and interaction between parties engaged in communication.

Communication theory studies the principles and patterns of information transmission in communication systems. It explores the optimal methods of transmitting a message from the source to the destination, in particular, ways to reduce the impact of noise and distortions on the quality of information transmission. Communication theory stresses that the successful transmission of a message depends on a strong connection between the source and the destination. The better the connections between these two elements are established and optimised, the more likely it is that the destination will receive the same message that was sent from the source. This means that the effectiveness of communication depends on the quality of communication between the parties and the optimal usage of the resources available for information transfer [20, 22].

The communication activity of an intelligent system can be considered as the act of establishing a dependency between input and output data in the following cases [12, 21]:

1. When an intelligent system exchanges information between its components or subsystems of an intelligent system. The input data that is received by the system can be processed, and the result of this processing becomes the output data for other components or subsystems of the intelligent system.
2. When an intelligent system interacts with its environment through input and output data. The input data represents information that the system receives from the environment, and output data reflects the results of the activity of the intelligent system that affects the environment [20].

In these cases, the communication activity of the intelligent system consists in establishing the dependency between input and output data, ensuring the transfer and exchange of information between different parts of the intelligent system or between the system and the environment [24]. In the image presented in fig. 2, you can see the main structure of the subsystem of the intelligent system from the point of view of communication. System input and output consist of two limited sets of events. One set of events reflects possible input events that affect the system from the environment or other subsystems of the intelligent system [8, 22]. The second set of events represents the possible output events that the system can generate as a result of its activity. Then, communication theory demonstrates that the dependency between events in a set influences the number of possible input or output signals that can be constructed. The more dependencies there is between the events in the set, the fewer different options for input or output signals can be constructed. Conversely, if the dependencies between events are smaller, the number of possible input or output signals increases [15, 24, 33].

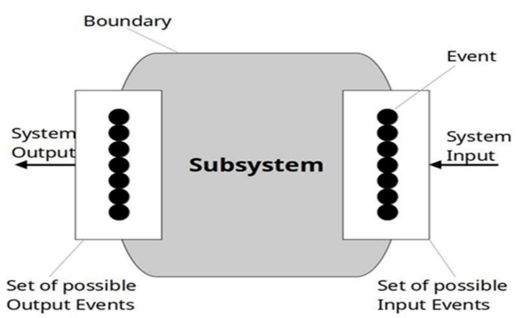

Figure 2. Architecture of a subsystem of the intelligent system. (The drawing was created using the vector graphics editor LibreOffice Draw)

Communication theory examines these dependencies and helps understand how changing dependencies between events influences the ability to transfer information between a system and its environment or subsystems.

In order to present subsystems of an intelligent system as communication systems, it is necessary to describe the activity of subsystems from the point of view of communication [8, 15, 24]. This approach considers the interaction between subsystems of an intelligent system as a form of communication, where information is exchanged and dependencies are established.

Treating subsystems of the intelligent system as communication systems allows analysing and modelling their behaviour from a communication perspective. This provides a unified framework for studying the effectiveness and interaction of various subsystems of an intelligent system, regardless of their specific nature or functionality [6].

The concept of communication systems provides a common language for describing the behaviour and dependencies of subsystems of an intelligent system within a larger intelligent system. It allows us to study how information flows between subsystems of an intelligent system, how dependencies are established and optimised, and how the overall efficiency of the system depends on these communication actions. Considering subsystems of an intelligent system as communication systems allows to describe the behaviour and interaction of subsystems using the language of communication. This allows us to study how information is transferred between subsystems of an intelligent system, how dependencies are established and optimised, and how these communication processes affect the overall efficiency of the system [7, 23].

Representation of an intelligent system as a communication system is implemented by identifying the input and output events of the system. This process involves analysing what data comes into the system from its environment (input events) and what data it generates or transmits to the outside (output events). After identifying these events, the system can be considered as a communication system, where interaction between subsystems occurs in the form of information exchange and establishment of dependencies.

In order to consider an intelligent system as a communication system, it is also necessary to describe the ways of interaction between the subsystems of the intelligent system in terms of communication. This includes the determination of the ways to exchange information between the subsystems of the intelligent system, establishing dependencies and optimising them. The use of the communication perspective allows to explore the behaviour and interaction of different subsystems of an intelligent system within the framework of a single system, regardless of their specific nature or functionality. The first step in the approach to intelligent systems is the determination of the communication perspective (Fig. 3). This means a review of the intelligent system from the point of view of interaction and exchange of information between its components and subsystems of the intelligent system [17].

There are clear boundaries that define a subsystem and separate it from the environment and other subsystems. A communication source (*X*) is a component that includes all possible input events coming to the system from the environment,

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including other subsystems. A communication destination (Y) is a component that represents all possible output events of a subsystem to the environment, including other subsystems of the intelligent system Cooperation and data exchange between subsystems of the intelligent system is the basis for the functioning of the intelligent system [7, 23]. Considering a system from a communication perspective helps to better understand how information is communicated, how dependencies are formed, and how this affects the system's performance and efficiency.

The events that occur are the source of input and output data of the subsystem of the intelligent system and they influence its operation and interaction with the environment or other subsystems of the intelligent system. Input events are stimuli or information entering the subsystem of an intelligent system, while output events are the result or response to the activity of the subsystem [6].

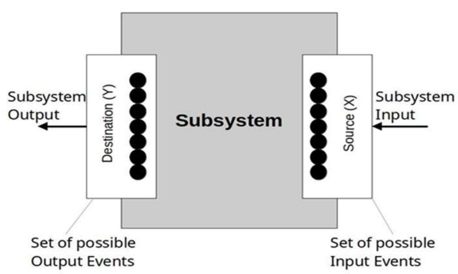

Figure 3. Presentation of the intelligent system subsystem as a communication system. (The drawing was created using the vector graphics editor LibreOffice Draw)

The set of input events is a source of communication for the system, because it includes all possible events that can influence the subsystem of the intelligent system from the outside or from other subsystems of the intelligent system. The set of output events, for its part, reflects all possible results or responses of the subsystem of the intelligent system to input stimuli.

The behaviour of the system is determined by how the subsystem of the intelligent system reacts to input events and generates corresponding output events. It describes how the subsystem operates, how it interacts with the environment, and how it transforms input information into output results [8, 11]. The behaviour of the system can be considered as a set of connections between input and output events that reflect specific functionality and reactions of the subsystem of the intelligent system to stimuli.

Communication theory studies the movement and processing of information between the source and the receiver, and it also measures the activity of this process. Entropy, according to the communication theory, indicates the number of possible ways of forming a message from a set of symbols. The higher the entropy, the more options a message can create. The high-entropy character set has no restrictions or rules, so there is the biggest number of possible messages. However, the application of rules and restrictions reduces entropy because the number of possible combinations of symbols is limited. Thus, entropy reflects the diversity and irreversibility of the formation of messages from a set of symbols [7].

Symbols are treated as events that occur in the system. A message is a combination of these events that can be used as input or output data of the system. In this case, entropy measures the amount of information needed to describe possible combinations of input or output data [22]. As the dependencies between events in a set increase, the number of possible combinations decreases and the entropy of the set decreases. This means that the more restrictions and dependencies are established between events, the fewer options for combinations of input or output data can be created [11, 24].

In general, entropy reflects the degree of uncertainty or diversity in the possible combinations of events. The higher the entropy, the greater the variety of possible combinations, and the lower the entropy, the more restrictions and dependencies are established, which leads to a reduction in the number of possible combinations.

The entropy of the source $H(X)$ and the receiver $H(Y)$ is determined based on the number of events in the respective sets and the probabilities of their occurrence. The number of events in the source and their probability determine the entropy of the source. Each source input is input data for to the system. The number of events at the receiver and their probability determine the entropy of the receiver. Each receiver output represents a system output.

The form of presenting information is called a message. A message is a set of signs or primary signals containing information [7]. Messages are divided into discrete and continuous. The subject or object that generates information and presents it in the form of a message is called the source of information. A discrete source of information has a finite alphabet consisting of n elements $x_1, x_2, ..., x_n$; each one of those is characterised by probabilities $P(x_1), P(x_2), \dots, P(x_n)$.

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It is convenient to present the set of elements and their probabilities in the form of a matrix:

$$\left\|\begin{matrix} X \\ P \end{matrix}\right\| = \left\|\begin{matrix} x_1 \; x_2 \cdots x_n \\ P_1 P_2 \cdots P_n \end{matrix}\right\|, \quad (1)$$

The partial entropy, which is the greater the lower the probability of $P(x_i)$: is, acts as the numerical characteristic of the uncertainty of the appearance of the element x_i:

$$H(x_i) = -\log_a(x_i), \quad (2)$$

For the entire set of discrete messages, uncertainty is determined by entropy, which is calculated by averaging the probabilities of partial entropies (2):

$$H(x) = -\sum P(x_i) \log P(x_i), \quad (3)$$

Entropy (3) meets the requirements for the degree of uncertainty. It is equal to zero when the probability of one value of x_i is equal to one, and the probability of other values is zero, that is, when we have a message without alternatives. Entropy is maximal if all messages are equally likely, i.e.: $P(x_1) = P(x_2) = \dots P(x_n) = \frac{1}{n}$.

Meanwhile, entropy:

$$H(x) = -\sum \log \frac{1}{n} = \log n, \quad (4)$$

The choice of the base of the logarithms is unimportant. It is common to use binary logarithms and to define the amount of entropy in bits. While calculating entropy, unlikely results can be excluded without much error. The contribution of the components of formula (3), for which $P(x_i) > 0{,}95$ or $P(x_i) < 0{,}05$, can be neglected [11, 23].

Messages transmitted by continuous signals are continuous. A continuous message as a random process is described by the density $f(x)$ of the probability distribution [6, 7, 8].

Let's divide the range of values of a continuous message into small sections Δx_i. The probability of the message value falling into the interval Δx_i is approximately equal to $f(x_1) \cdot \Delta x_1$, where $f(x_1)$is the probability density for the point lying in the middle of Δx_1. Then the entropy of a continuous message can be defined as:

$$H(x) = \lim_{\Delta \to 0} (\textstyle\sum_i f(x_i) \Delta x_i \log f(x_i) \Delta x_i =$$
$$= -\int_{-\infty}^{\infty} f(x) \log f(x) dx - \int_{-\infty}^{\infty} f(x) dx \lim_{\Delta x \to 0} \log \Delta x, \quad (5)$$

Given that $\int_{-\infty}^{\infty} f(x) dx = 1,$ we will get:

$$H(x) = -\int_{-\infty}^{\infty} f(x) \log f(x) dx - \lim_{\Delta x \to 0} \log \Delta x =$$
$$= h(x) - \lim_{\Delta x \to 0} \log \Delta x, \quad (6)$$

The first component of expression (6) is called the differential entropy of a continuous message. The second component at $\Delta x = const$ acquires a constant value and is excluded from consideration [7, 9, 14, 15]. If the distribution law of the quantity X is uniform, then the probability density is:

$$f(x) = \frac{1}{x_{\max} - x_{\min}}, \quad (7)$$

Differential entropy of a uniformly distributed quantity:

$$h(x) = -\int_{\min}^{\max} \frac{1}{x_{\max} - x_{\min}} \cdot \log \frac{1}{x_{\max} - x_{\min}} dx = \log(x_{\max} - x_{\min}), \quad (8)$$

And the total entropy:

$$H(x) = h(x) - \log\Delta = \log \frac{x_{\max} - x_{\min}}{\Delta}, \quad (9)$$

For the normal distribution law:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma(x)}} \ell 2\sigma^{\frac{x^2}{2(x)}}, \quad (10)$$

where $\sigma(X)$ is the standard deviation of X values. Differential entropy:

$$h(x) = -\int_{x_{\min}}^{x_{\max}} f(x) \Delta \log f(x) dx = \log\left[\sqrt{2\pi\ell}\, \sigma(x)\right], \quad (11)$$

Total entropy:

$$H(x) = h(x) - \log\Delta = \log \frac{\sqrt{2\pi\ell}\, \sigma(x)}{\Delta}, \quad (12)$$

If the sequence of characters of the alphabet is not independent (for example, in foreign languages, the letter «q» is almost always followed by «u»), the uncertainty of the message (and therefore the entropy) decreases. In this case, conditional entropy is used. The statistical relationship between the expected message and the previous message is quantified by the joint probability $P(x_i,\ x_i)$ or the conditional probability $P\left(\frac{x_i}{x_i}\right)$, which expresses the

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probability of the appearance of the message element x_i under the condition that the previous element was x_i. The partial entropy according to (2) will be equal to:

$$H(\frac{x_i}{x_j}) = -\log P\frac{x_i}{x_j}, \quad (13)$$

Next, we average the partial entropy. We get the entropy of the X message under the condition that the element x_i was present:

$$H(\frac{x_i}{x_j}) = -\sum P(\frac{x_i}{x_j})\log P\frac{x_i}{x_j}, \quad (14)$$

Finally, we average the entropy (14) over the probabilities of the previous appearance of all possible elements:

$$H(\frac{x_i}{x_j}) = -\sum P(x_j)\sum P(\frac{x_i}{x_j})\log P\frac{x_i}{x_j}, \quad (15)$$

An important property of the conditional entropy of the source of dependent messages is the fact that with an unchanged number of message elements, entropy decreases with an increase in the number of elements between which there is a statistical relationship. Using the concept of conditional entropy, we can determine the entropy of the combined system through the entropy of its component parts [6, 16, 18, 25]. If two systems X and Y are combined into one, then the entropy of the combined system is equal to the entropy of one of its constituent parts plus the conditional entropy of the second part relative to the first:

$$H(X,Y) = H(X) + H\left(\frac{Y}{X}\right), \quad (16)$$

In the special case when systems X and Y are independent, $H\left(\frac{Y}{X}\right) = H(Y)$, we have the entropy addition theorem:

$$H(X,Y) = H(X) + H(Y), \quad (17)$$

For the entropy of the source $H(X)$:

1. The number of different events or symbols in the source is determined.
2. The probability of occurrence of each event is determined.
3. The Shannon entropy formula is used to calculate the entropy of the source:

$$H(X) = -\sum_{n=1}^{N} p_n \log_2 p_n, \quad (18)$$

where p_n is the probability of occurrence of the n^{th} event.

Similarly, for the receiver entropy $H(Y)$:

1. The number of different events or symbols in the original set is determined.
2. The probability of using each event is determined.
3. The Shannon's entropy formula is used to calculate the entropy of the receiver:

$$H(Y) = -\sum(p_n \cdot \log_2 p_n), \quad (19)$$

where p_n is the probability of using of the n^{th} event.

The obtained entropy values reflect the number of bits needed to describe possible variants of input and output signals of the system [8, 10].

Communication theory defines joint entropy as a measure of the relationship between two sets of events X and Y. It is measured by the number of bits needed to describe all available dependencies between the system's inputs and outputs.

When the system interacts with the environment and establishes more dependencies between its source and destination, the joint entropy decreases [7, 20, 21]. This happens because increasing dependencies between inputs and outputs causes a decrease in the number of available combinations of input and output events. Dependencies set restrictions and rules for the use of symbols (events), which reduces the number of possible ways to construct messages. Thus, the joint entropy decreases when the system interacts with the environment and more dependencies between the source and the destination are defined (Fig. 4).

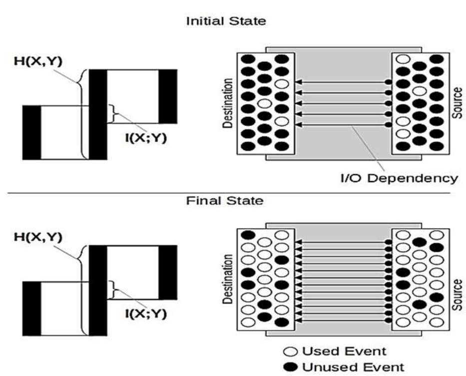

Figure 4. Changes in communication entropies. (The drawing was created using the vector graphics editor LibreOffice Draw)

In the initial state, the system has a low level of dependency between the input and output data, so the value of the joint entropy is higher than in the final state. This is the opposite for mutual information, which grows as the system establishes more dependencies between input and output data.

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The interaction of subsystems of the intelligent system with their environment leads to changes in the entropy of the source and destination of the subsystem of the intelligent system, as well as in mutual information. Specifically, such interaction can have the following consequences [11, 19]:

1. Change in the entropy of the source: the interaction can change the number of possible input events (inputs) that influence the subsystem of the intelligent system. This results in a change in the entropy of the source, i.e. the number of bits needed to describe the various possible input events.
2. Change in the destination entropy: interaction can also change the number of possible output events (outputs) that can be generated by the subsystem of the intelligent system. This results in a change in the entropy of the destination, i.e. the number of bits required to describe the various possible output events.
3. Change in the mutual information: the interaction affects the degree of interdependency between the input and output events of the subsystem of the intelligent system. This mutual dependency is measured by mutual information, which demonstrates to what degree information about input events helps predict output events and vice versa. Interaction can change the level of mutual information, reflecting the change of connections and dependencies between events.

In communication theory, capacity is denoted by the symbol «C» or «Capacity». This symbol is used to indicate the level of dependency between the source and the destination, that is, a measure of the system's communication capability [22]. The quantity that determines the capacity of communication is mutual information:

$$\text{Communicat ion Capacity} = I(X;Y), \tag{20}$$

Entropy and information are calculated using Shannon's formulas; their unit of measurement is a bit [23]. Entropy is used to measure the degree of uncertainty or diversity of a random variable. In the context of communication, entropy describes the number of bits needed to represent different possible inputs or outputs of a system [7, 16, 18].

On the other hand, information is used to measure the dependency between two sets of data. It indicates the extent to which information about one set helps to reduce uncertainty or resolve questions about another set. Information is also measured in bits and is used to analyse dependencies and optimise communication systems. Hence, entropy is used to describe the statistical characteristics of inputs or outputs, while information is used to measure the dependence between those inputs and outputs.

Efficiency is a measure of how well an intelligent system uses limited resources to achieve its goals and sustain its activities. This is an assessment of how economically and efficiently the system uses available resources like time, money, materials, labour, etc. to perform its tasks [7, 23].

Efficiency can be measured in different contexts, depending on the nature of the intelligent system and its goals. For example, a production system can be considered effective if it achieves high productivity and minimises resource consumption. A management system can be considered effective if it makes quick and accurate decisions based on available information. Efficiency is based on optimal use of resources, minimisation of losses and maximisation of results [16].

The overall efficiency of an intelligent system can be measured by various indicators, such as profitability, productivity, quality, the ratio of costs to results, etc. These indicators help assess how effectively the system is using its resources and if it is achieving its goals. From the perspective of entropies, the actual input-output dependency is determined by mutual information, and the source-destination joint entropy determines the maximum input-output dependency.

$$Communicat\,ion \quad Efficiency = \frac{Chaimel \quad Capacity}{Input} - \tag{21}$$
$$- Output \quad Join\,ty \quad Entropy \quad = \frac{I(X;Y)}{H(X,Y)},$$

This ratio determines the communication efficiency of the subsystem of the intelligent system. Given a fixed size of input and output event sets, increasing communication efficiency is achieved by increasing communication capacity (input/output dependencies). On the other hand, increasing the size of the input and output event sets (increasing $H(X)$, $H(Y)$, or both, hence $H(X,Y)$) directly reduces the communication efficiency of the system, but not necessarily its communication capacity [3, 9, 18]. Communication theory states that due to noise, the channel capacity will always remain less than the joint entropy. Accordingly, the communication efficiency is always less than 1.

The flexibility of an intelligent system reflects its ability to adapt to changes in working conditions in order to achieve its goals.

This means that the system can change its activity in response to changes in the environment or internal conditions [8]. To achieve flexibility, the intelligent system uses its resources and adaptation mechanisms. Resources can include knowledge,

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algorithms, models, skills, and other elements that enable the system to understand and respond to change. Adaptation mechanisms include methods, algorithms, and strategies that a system uses to change its activities depending on new conditions.

The system can adapt its activities to changes by reconstructing its models, changing algorithm parameters, restoring or changing knowledge, and using data-driven learning. These mechanisms allow the system to respond to new requirements, solve new tasks and adapt to changes occurring in working conditions [22, 24].

The adaptability of an intelligent system at any point in time depends on several factors and the resources at its disposal. The main factors that affect the adaptability of the system include [7, 8, 13, 15]:

1. Resources and knowledge: An intelligent system can have access to a variety of resources, such as databases, knowledge, models, algorithms, and other elements that help it understand its environment and make appropriate decisions. Richer resources and a larger knowledge base can increase the system’s adaptability.
2. Adaptation mechanisms: an intelligent system must have effective adaptation mechanisms at its disposal (for example, learning algorithms, parameter change strategies, model reconstruction methods, etc.). These mechanisms allow the system to make changes in its activity and adapt to new conditions.
3. System architecture: the architecture of an intelligent system can influence its adaptability. A flexible architecture that allows you to quickly and easily change system components or implement new functions helps improve adaptability.
4. Tracking and updating: an intelligent system must be able to track changes in its environment and update its models and knowledge accordingly. This can include gathering new data, re-evaluating existing knowledge and models, incorporating new information sources, etc.
5. Reduction of reaction time: the adaptability of an intelligent system also depends on its ability to quickly respond to changes in operating conditions. Minimisation of the reaction time can help an intelligent system adapt faster and more efficiently.

All these factors interact with each other and influence the level of adaptability of the intelligent system [21]. The better are resources and mechanisms of adaptation and renewal that the system has at its disposal, the more likely it will be to easily adapt its activities to changes in its environment and achieve its goals.

Since flexibility is considered to be a relative value here and it is defined as the ratio of unused communication resources of the intelligent system to the available communication resources of the system [1, 7, 10]. A system with 20% flexibility means that 20% of the system's communication resources remain unused and can be used to interact with the environment. Thus, the communication capacity of the system determines the used communication resources of the system, so the unused communication resources are equal to the difference between the available communication resources of the intelligent system $H(X,Y)$ and the used resources:

$$Used\quad Communication\quad Resources = H(X,Y) - I(X;Y), \tag{22}$$

$$Communication\quad Flexibility = H(X,Y) - \frac{I(X;Y)}{H(X,Y)} = \\ = 1 - Communication\quad Efficiency, \tag{23}$$

The flexibility of communication reaches its maximum (it is equal to one) when the input and output sets of events are completely independent of each other [19, 24]. This means that the system has not yet established any dependencies between input and output events. A situation like this occurs at the initial stage of communication, when the system has not yet defined any exchange dependencies between its source and destination. However, with the development of the system and the establishment of dependencies between input and output events, flexibility decreases, as the system becomes more and more dependent on established connections [12].

However, it is worth noting that in real communication systems, maximum flexibility (complete independence) is a theoretical ideal, since noise is always present in any communication. This means that an intelligent system can never achieve complete independence between its input and output events.

The determination of the system's communication state diagram is based on concepts related to the behaviour of the complex adaptive systems (CAS). It is believed that the CAS have undergone a life cycle during which the relationships and dependencies within the system change as they interact and adapt to their environment [2, 14, 25]. CAS are characterised by the fact that they have a life cycle in which the relationships and dependencies in the system change during its interaction and adaptation to the

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surrounding environment. CAS include a variety of systems, including intelligent systems, social networks, biological systems, and others [3, 7, 23].

The definition of the system's communication state diagram is based on these concepts, since the communication processes in the system are complex and adaptive. The communication state diagram shows the dependencies between communication variables, such as communication efficiency, flexibility, and capacity of communication, which can change depending on the system's interaction with its environment. This allows for a better understanding and analysis of communication processes in the system, taking into account its adaptive behaviour, which is important for the development and improvement of intelligent systems and other complex systems [19, 23, 25].

For each specific subsystem of an intelligent system, there will be a point on the diagram that represents the communication state in which that system can exist. The horizontal axis usually reflects the efficiency and flexibility of communication and has a range of values from zero to one. Changes in the size of the input and output event sets are shown on this axis because they directly affect the efficiency and flexibility of the system. Communication capacity is expressed in bits on the vertical axis and determines the level of dependence between the input and output of the system. This image can be used to determine the value of the communication capacity and efficiency of the subsystem of the intelligent system located at the point (SI). When interacting with the environment, the subsystem of the intelligent system can establish new dependencies between input and output. These new dependencies increase the communication capacity of the subsystem and, accordingly, increase the communication efficiency. This puts the system into a new communication state, such as (S2). When a subsystem of an intelligent system is in state (S2) and encounters new conditions in the environment or interacts with other subsystems of an intelligent system, its capabilities and responses are different from when it encountered the same new conditions while in state (SI). In the (SI) state, the intelligent system's subsystem has more flexibility and freedom to use free input and output events to build the necessary input-output dependencies to cope with new conditions.

However, this does not apply to the situations where the subsystem of the intelligent system is in state (S2). In this case, the subsystem of the intelligent system has fewer available communication resources. It can take two courses of action: either break some input-output dependencies (or reformulate them to accommodate the new changes), or expand its communication resources by expanding the sets of input and output events. Both options influence the communication efficiency of the system, and this can lead to the transition of the system to the state (S3).

Communication state reflects the system's activity by registering changes in its input or output events, regardless of the origin or meaning of those changes. These changes can be the result of new events or changes in the probability of occurrence of already existing events (frequency of their occurrence) [8, 20]. In the case of a communication system, the meaning of the event itself does not matter, only the relationship and dependency between them is important. This allows us to determine the state of communication for systems of different nature and analyse them from the same perspective.

Fig. 5 shows an example of visualisation of the interaction of subsystems of an intelligent system within the boundaries of the intelligent system from a communication perspective. The presented subsystems of the intelligent system are considered to support a certain process carried out by the intelligent system [4, 23]. Representation of subsystems as communication systems indicates the general communication behaviour of the process and its interconnection with the communication behaviour of the corresponding subsystems. Representation of subsystems as communication systems also indicates that the interaction and exchange of information between subsystems is a key element of their functioning and interaction.

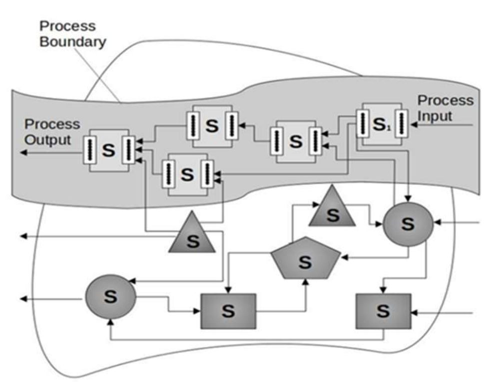

Figure 5. Analysis of intelligent system communication. (The drawing was created using the vector graphics editor LibreOffice Draw)

This emphasises that an important aspect of the operation of any intelligent system is not only the

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components themselves, but also the way in which they communicate with each other. Addressing the subsystems of the intelligent system as communication systems allows us to focus on the interaction and exchange of information between them, to understand how this interaction affects the operation of the intelligent system as a whole and what changes occur within the system during this interaction [7, 9, 22]. It is suitable for the analysis and modelling of intelligent systems with diverse natures and structures, which contributes to understanding their behaviour and influencing them effectively.

To apply this approach to process performance analysis, the following components are determined for each of the interacting subsystems of the intelligent system [10, 24]:

- Sets of input and output events.
- Input and output data with corresponding probabilities.
- Input-output dependencies (interconnection between input and output data) and their corresponding probabilities.

Based on the given values, the communication entropies are determined and the communication state of each subsystem of the intelligent system is established. In the case of a change in the input signal of the process, a change like this can take the form of a new input event for the SI subsystem. This new event increases the entropy $H(X)$ of the SI source, which in turn reduces the efficiency of the subsystem. Initially, the communication capability is affected by the fact that a new event is used to define a new input-output relationship or is incorporated into an existing one. Both of these changes influence the overall communication state of the subsystem. Analysis and changes in dependent subsystems during the process can be tracked using the same approach [6, 15].

Thus, the communication entropies and the communication state of each subsystem of the intelligent system are determined based on the values associated with the interaction and exchange of information within the system. Usually, parameters like the number of messages, their distribution, the information value of messages, etc., are used to determine the communication entropy. These values reflect the degree of uncertainty and variety of information transmitted between the subsystems of the intelligent system. The state of communication of each subsystem of the intelligent system is established based on the measurement of communication entropy and other relevant parameters [1, 5, 7, 11, 16]. This state reflects the efficiency and quality of communication within the subsystem of the intelligent system, as well as its interaction with other subsystems. Changes in the values of these parameters indicate changes in the communication state of the subsystem, which may be caused by changes in input events, input-output dependencies, or other factors affecting the exchange of information. Therefore, the value of communication entropy and the analysis of the communication state help to understand how efficiently communication occurs within the subsystems of the intelligent system and the intelligent system as a whole, as well as how it can change according to changes in input parameters and dependencies [8, 23].

In general, depending on the analytical question, separate subsystem within an intelligent system, a process that includes several subsystems of an intelligent system, or for the entire intelligent system as a whole [23]. In general, depending on the analytical question, it is possible to define communication states for a separate subsystem of an intelligent system within an intelligent system, a process that includes several subsystems, or for the entire intelligent system as a whole [11].

5. CONCLUSIONS

The study confirms that the communication state of the system reflects any changes that occur within the intelligent system during its interaction with the environment. Although the conclusions presented in this approach are theoretical and have not been empirically confirmed or tested, their validity is based on the principles and results of the known communication theory.

According to the Shannon-Weaver theory of communication, the main purpose of communication is to influence the receiver's behaviour in order to achieve the desired result. The theory states that while influence depends on the meaning of the messages exchanged between the sender and the receiver, the technical aspect of communication (concerning the transmission and reception of information) plays an important role in facilitating this influence.

Considering an intelligent system as a communication system, the nature of events within the system becomes less significant compared to their interconnection and interdependence. This perspective allows us to determine the state of communication and facilitates the modelling and analysis of systems of different nature using a unified approach.

It is important to note that further research and practical trials are needed to confirm the conclusions that were made in this paper. However, the proposed approach is based on the established principles of communication theory and provides a promising basis for understanding and evaluating the behaviour of an intelligent system from the point of view of communication.

Thus, this work opens an intriguing path for further research in the field of communication in intelligent systems, yet it distinguishes itself from previous studies through its focus on the theoretical aspects of communication and their impact on intelligent systems. The conclusions of this work lay a theoretical foundation for future investigations and differentiate themselves from prior knowledge by emphasizing the principles and outcomes of well-established communication theory, notably Shannon and Weaver's theory. This concept encourages thorough scholarly analysis and may pique the interest of researchers concerned with the development of intelligent systems and their interaction with the surrounding environment. Nevertheless, it is essential to acknowledge that these theoretical findings serve as a starting point for further research, and the practical applicability of this approach necessitates more rigorous investigations and real-world testing.

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