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Energy Consumption Monitoring with Evaluation of Hidden Energy Losses

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ABSTRACT This article presents a computational method for monitoring the energy consumption of technological systems with the assessment of their hidden energy losses caused by erroneous actions of personnel or equipment failures. Herewith, energy losses are calculated as the difference between the actual energy consumed and the minimum energy required to conduct the process in all operating modes. The minimum required energy is determined by the machine learning method based on stationary consumption precedents. Two approaches to the implementation of energy consumption monitoring with the assessment of hidden energy losses are considered – hardware and software. The hardware approach is based on the preliminary definition of normative, or minimum specific energy consumption in each technological mode. The software approach is based on the modeling of stationary areas of energy consumption in the form of precedents and their further analysis in the space of influential technological parameters. The paper notes the advantages and disadvantages of the proposed monitoring method, it is emphasized that the method is able to work with both linear and non-linear functions of energy dependence on the parameters of the technological process. It is noted in the paper that the advantage of the proposed method is the automated construction of the minimum energy function.

KEYWORDS monitoring; energy consumption; precedents; energy losses.

I. INTRODUCTION

IN modern conditions of increasing the cost of energy resources and the transition to high-tech industries, energy efficiency is becoming a particularly important issue. The main driving force for improving energy efficiency at the enterprise is energy management, but one of the obstacles to its development is that energy management does not apply to specific technological systems – energy consumers. The energy efficiency of individual technological systems is assessed periodically, only during energy audits. A promising approach to the methodology of energy management is the introduction of continuous, "smart" monitoring of energy efficiency of technological systems to respond quickly to the deterioration of their technical condition and violation of the technological regime [1].

The technological system functionally unites technological equipment, production products and performers into a single production process. Each of these links can affect energy consumption and energy losses. The operation of the technological system is considered effective if the non-technological, hidden energy and raw material losses are absent or minimal. Otherwise, the operation of the equipment is considered inefficient [23].

Hidden energy losses in the technological system [2] can be caused by violations of the technical conditions of equipment, deterioration of raw material properties, erroneous actions of personnel, and other hidden factors $Z = \{z_1, \ldots, z_n\}$, which are usually not subject to automated control. But the automated control is subject to adjustable parameters $X = \{x_1, \ldots, x_k\}$, which determine the modes of the technological process. Accordingly, the energy consumption E of the technological system can be described by the dependence:

$$E = f(X, Z). \tag{1}$$

Therefore, to prevent a drop in energy efficiency of the technological system, it is important to timely diagnose and eliminate changes in energy consumption of equipment caused by the appearance of hidden unregulated factors. The occurrence of hidden energy losses can characterize changes in the technical conditions of the equipment [3].

II. KNOWN MONITORING METHODS

Automated systems for monitoring the energy consumption of the enterprise consist of energy consumption meters of individual technological groups and means of calculating the obtained data. Some companies develop specialized software that supports energy monitoring systems. The well-known software [4, 5] is designed to track energy consumption, optimize performance, and remote control of equipment for both small homes and large industrial energy consumers. In the process, it combines data about the distribution networks of the enterprise and presents them in the form of clear information through an intuitive web interface.

Known software [6, 7], which allows to visualize energy flows in technological processes, assign them to the appropriate consumers or cost centers and determine why there have been changes in energy consumption. Also, there are known approaches to monitoring the process of energy consumption as a stream of precedents [8]. But these systems have limited ability to estimate energy losses in technological systems, which reduces the possible efficiency of energy management.

There are systems that determine the current mode of operation linking the monitoring of energy consumption with the paradigm of the Internet of Things. This results in automated systems that allow to control and manage power-consuming devices connected to the Internet via Wi-Fi [9].

In the process of monitoring energy consumption, the current values of energy consumption are compared with certain indicators. Thus, a computing monitoring system [10] has been patented, which is able to store the values of the baseline energy consumption for each of the operating modes and compare them with the current values. In the event that the current value of energy consumption exceeds the allowable threshold, the system warns service personnel of the anomaly.

There is a method of monitoring energy efficiency, in which the reference value of energy consumption is obtained by testing the process system and which does not change during the entire period of operation of the equipment. The disadvantage of this method is that the conditions and modes of operation of technological systems at different enterprises can change in a wide range, which accordingly leads to changes in energy consumption, which are considered acceptable and efficient at the enterprise [11].

In operational energy management, a monitoring method can sometimes be used in which the actual current energy consumption is compared with the energy consumption obtained by the calculation method according to known empirical or analytical dependences of electrical engineering, heat engineering, mechanics, hydraulics [12]. This method gives an approximate estimate of the reference energy in the real technological process [22].

In most cases, energy management uses a linear regression model of the dependence of "standard" energy consumption on controlled technological parameters according to the "Monitoring and Targeting" method [13] for comparison with current energy consumption. There are automated monitoring and targeting systems compatible with the ISO 50001 standard. The "Monitoring and Targeting" methodology consists in a systematic approach to the use of energy resources to achieve the best economic result [14].

This work considers a new approach to monitoring energy consumption of technological systems based on machine learning [24] and analysis of precedents [26] of stationary energy consumption. The essence of this approach is to determine the hidden energy losses of the technological system by comparing the current energy consumption with a precedent-analytical model of effective energy consumption, which is formed in the process of machine learning.

This paper considers a new approach to monitoring the energy consumption of technological systems of the enterprise based on the hardware and software platform for determining the hidden energy losses of the enterprise. The essence of this approach is to calculate the hidden, non-technological energy losses in each controlled technological system and the formation of an integrated profile outside the technological energy losses of the enterprise. The hardware and software modules are based on different approaches to monitoring.

III. STATEMENT OF THE PROBLEM

The stationary energy state, or stationary specific energy consumption $\boldsymbol{E}$ of the technological system depends on the set of influential technological parameters $\boldsymbol{X}$ and the set of uncontrolled factors $\boldsymbol{Z}$ that cause hidden energy losses $\boldsymbol{\Delta E}$.

$$E = f\,(X, Z) = \varphi\,(X) + \Delta E. \qquad (2)$$

Energy consumption with unchanged influential technological parameters $X=const$ will be called the steady state of energy consumption. At certain points in time, when the vector of technological parameters X changes, or factors Z appear, the system is able to move from one stationary state of energy consumption to another:

$$E_i = \varphi\,(X_i) + \Delta E_i \rightarrow E_j = \varphi\,(X_j) + \Delta E_j. \qquad (3)$$

Energy consumption with unchanged influential technological parameters X=const will be called the steady state of energy consumption. Energy consumption is considered efficient when the hidden energy losses are zero $\Delta E = 0$. The task of monitoring is to assess the hidden energy losses by constantly comparing the current energy costs with the minimum costs for a given technological regime, or achieved in the past, or obtained empirically:

$$\Delta E = E_i - min\,E_i. \qquad (4)$$

IV. PRECEDENT-ANALYTICAL METHOD OF ESTIMATING HIDDEN ENERGY LOSSES

In the case-analytical method of estimating hidden energy losses, it is assumed that there is a regression of effective energy consumption on influencing factors, which we will call the function of effective energy consumption and which is the minimum actual energy consumption at different values of influencing factors. Knowing the function of effective energy consumption, it is easy to calculate energy overspending for any time interval using the formula:

$$\Delta E_i = Emin(X_i) - E_i = a + b(X_i) - E_i,$$

where a and b are regression coefficients; X_i and E_i are influence and energy consumption factors for the i-th time interval.

The precedent of stationary energy consumption is a case in the technological system in which all factors of influence are in a stationary state. Hence, the precedent of stationary energy consumption has the following format:

$$CaseE = \left\langle \begin{matrix} M(X_1), & \dots, & M(X_n); \\ D(X_1), & \dots, & D(X_n); \\ r(X_1), & \dots, & r(X_n); \\ \mathrm{E}, & \tau, & S \end{matrix} \right\rangle, \tag{6}$$

where: $M(X_1), \dots, M(X_n)$ – mathematical expectations of the factors of influence $X_1, \dots, X_n$;

$D(X_1), \dots, D(X_n)$ – statistical variance of influencing factors $X_1, \dots, X_n$;

$r(X_1), \dots, r(X_n)$ – autocorrelation coefficients of influencing factors $X_1, \dots, X_n$;

E – specific energy consumption for the period of the steady-state;

τ – duration of the steady-state;

S – probable diagnosis of a technical condition.

Each stationary state corresponds to a point in the space of influential technological parameters. Functions of effective energy consumption are built according to the points of actual minimum consumption, actually achieved in practice. We consider all points above the effective energy consumption function to be overspends, or losses associated with suboptimal consumption of energy resources in the corresponding time intervals.

The essence of the method consists in teaching the monitoring system to recognize precedents of stationary energy consumption with minimal energy costs and building on their basis limited sections of the regression function of effective energy consumption.

Thus, the determination of energy losses is carried out on the basis of a comparison of the actual energy consumption in the technological equipment with the already achieved minimum consumption values, with the same influencing factors. At the same time, due to the use of the method of machine learning based on precedents, it becomes possible to automate the process of constructing the function of effective energy consumption in the form of a dynamic spline.

V. HARDWARE MODULE

With the hardware method of energy loss control in the technological system, we calculate the energy loss ΔE as the difference between the actual energy consumed and the minimum energy required to conduct the technological process in the current mode [25]. The minimum energy is determined by multiplying the specific energy consumption of products e_i produced in the i-th mode of the technological process by the productivity p_i i-th mode of the technological process and the duration t_i of technological equipment in the i-th mode according to the following formula [15]:

$$\Delta E = E_{cons} - \sum_{i=0}^{n} e_i \cdot p_i \cdot t_i, \tag{5}$$

where: E_{cons} – energy actually consumed for the technological process, according to the meter;

e_i – specific energy costs for production, in the i-th mode of the technological process;

p_i – productivity of technological process in the i-th mode;

t_i – duration of operation of the equipment in the i-th mode;

n is the number of permissible operating modes. The block diagram of the hardware module is shown in Fig. 1.

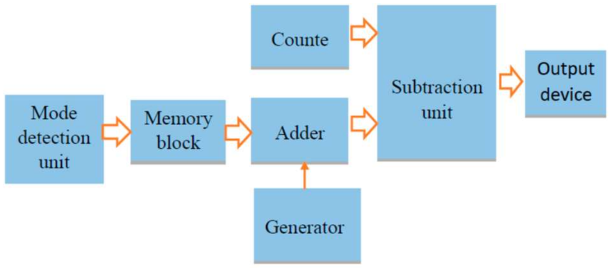

Figure 1. Block diagram of the hardware module

The proposed method of controlling energy losses in the technological process is implemented as follows. Preliminarily, the values of the specific energy consumption of the products produced in each of the possible modes of the technological process for one cycle of the time pulse generator are recorded in the storage unit. The module for estimating hidden energy losses is connected to the power supply input in series with the process equipment. After switching on the process equipment, the display unit displays the amount of non-standard energy losses caused by equipment malfunctions or violations of its regulation that occur in the process. Exceed of this allowable value signals to the personnel about the need to take preventive measures or replace the equipment.

VI. GENERALIZED DIAGRAM OF THE COMPUTER SYSTEM FOR MONITORING ENERGY CONSUMPTION

Computer monitoring of the efficiency of energy consumption of technological systems involves equipping them with counters of consumed energy and sensors of influential technological parameters. At the same time, the list of influential technological parameters is determined by specialists in the operation of technological equipment. For example, for a heating system, such parameters can serve as temperatures outside and inside the room, for a compressed air system – pressure in the main line and air flow. In the process of learning the system, the list of influential parameters can be refined.

A simplified scheme of the implementation of the monitoring system is presented in Fig. 2.

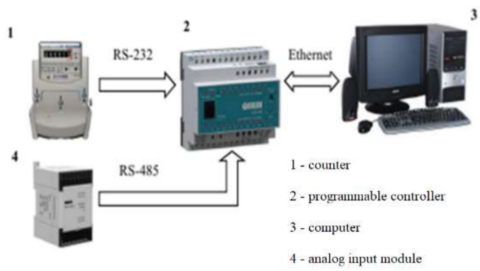

Figure 2. Simplified scheme of implementation of the monitoring system.

The hardware for operational monitoring of energy efficiency is represented by a programmable controller connected to a local energy metering center meter, an analog input module, and a top-level computer.

The meter is located together with the analog input module and the programmable controller in the local energy accounting center. The analog input module is designed for measuring analog signals from the sensors of the influence factors of the technological system. Measured data in the form of numerical series are transferred to the programmable controller. The programmable controller analyzes, by the well-known method [20], the numerical series that come from the analog input module for stationarity and forms precedent images from them.

VII. SOFTWARE MODULE

The operation of the hidden energy loss estimation software module is to cyclically perform the functions as shown in Fig. 3.

Obtaining information about the influential technological parameters is provided by the appropriate measuring and computing devices of the process control system. Both direct and indirect measurements can be used.

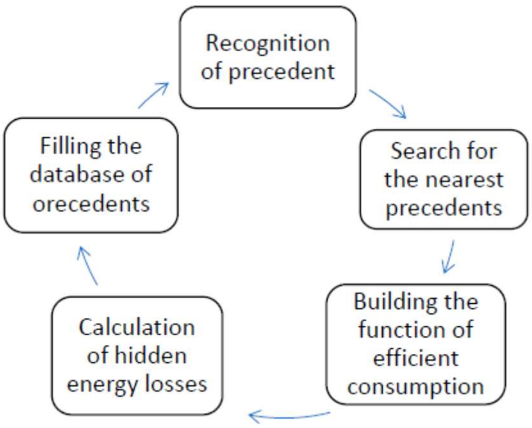

Figure 3. Scheme of the energy consumption monitoring cycle.

The precedent of stationary energy consumption is a case in the technological system in which all factors of influence are in a stationary state. Hence, the precedent of stationary energy consumption has the following format:

$$CaseE = \left\langle \begin{matrix} M(X_1), & \dots, & M(X_n); \\ D(X_1), & \dots, & D(X_n); \\ r(X_1), & \dots, & r(X_n); \\ \mathrm{E}, & \tau, & S \end{matrix} \right\rangle, \tag{6}$$

where: $M(X_1), \dots, M(X_n)$ – mathematical expectations of the factors of influence $X_1, \dots, X_n$;

$D(X_1), \dots, D(X_n)$ – statistical variance of influencing factors $X_1, \dots, X_n$;

$r(X_1), \dots, r(X_n)$ – autocorrelation coefficients of influencing factors $X_1, \dots, X_n$;

E – specific energy consumption for the period of the steady-state;

τ – duration of the steady-state;

S – probable diagnosis of a technical condition.

At the first stage of the monitoring cycle, the input flow of factors influencing $X_1, \dots, X_n$ is checked for stationarity by known methods of analysis [16]. After detecting the stationary power consumption mode, the moment of its beginning, mathematical expectations $M(X_1), \dots, M(X_n)$, variances $D(X_1), \dots, D(X_n)$ and autocorrelation coefficients of influencing factors $r(X_1), \dots, r(X_n)$, the specific energy consumption E are measured.

At the second stage of the monitoring cycle, the closest neighbors to the recorded actual precedent are searched in the precedent database [17]. It is believed that all precedents are located in the space of mathematical expectations of influencing factors. The search for the nearest neighbors to the actual precedent is performed according to the formula for calculating distances in the Euclidean space of mathematical expectations of influencing factors:

$$dM_{ij}(X) = \sqrt{\sum_{k=1}^{n} (M_i(X_k) - M_j(X_k))^2}, \tag{7}$$

where $dM_{ij}(X)$ – the distance between the influencing factors of the i-th actual precedent and the j-th precedent from the base of precedents. Thus, there are n precedents in the database of precedents, which are the closest neighbors to the actual precedent.

At the third stage of the monitoring cycle, the dependence of energy consumption on influential factors is approximated according to the data of the nearest precedents by the method of least squares [18]. The obtained function characterizes the dependence of the already achieved levels of efficient energy consumption on the technological parameters. Substituting the values of the technological parameters of the actual precedent into the obtained dependence, we obtain the calculated value of the effective energy consumption for the actual precedent.

At the fourth stage of the monitoring cycle, the presence of hidden energy losses is determined. To do this, calculate the difference between the energy consumption of the current precedent and the efficient energy consumption obtained by the calculation method at the previous stage. Depending on the result of the comparison, we conclude the energy efficiency of the equipment that is subject to monitoring. If the difference is equal to or less than zero, the equipment is considered to be operating efficiently, and the current precedent refers to the precedents of energy efficiency. If the difference is greater than zero, the equipment is considered to be operating at a hidden energy loss [19].

At the fifth stage of the monitoring cycle, the precedent database is filled with new precedents. Precedents are automatically added to the precedent database only if the equipment is operating efficiently. In all other cases, the decision-maker receives a notification describing the current situation to make a final decision on the cause of the energy loss.

The hardware for operational monitoring of energy consumption with the evaluation of hidden energy losses is represented by a programmable controller (3) connected to the meter (1) of the local energy metering center, the analog input module (2) and the top-level computer (4), as shown in Fig. 4.

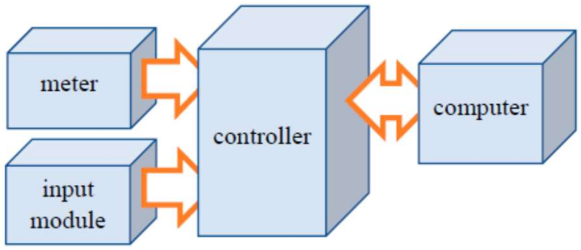

Figure 4. Scheme of the hardware for operational monitoring.

The meter is located together with the analog input module and programmable controller in the local energy metering center. For information exchange between the meter and the programmable controller, the serial standard RS-232 provided in the controller is used.

The analog input module is designed to measure analog signals from sensors of factors influencing the technological system. The measured data in the form of numerical series is transmitted via the RS-485 interface to the programmable controller.

The programmable controller analyzes by a known method [20] the numerical series coming from the module of the analog input to stationery and forms from them images of precedents.

VIII. LOSS ESTIMATION ALGORITHM

The hidden loss estimation algorithm is presented in Fig. 5. At the first stage of the monitoring cycle, which takes place in the programmable controller, the derivative flow of influence factors X1, ..., Xn is checked for stationarity in accordance with known methods of analysis [16]. After detecting the stationary power consumption mode, the moment of its onset, mathematical expectations M(X1), ..., M(Xn), variances D(X1), ..., D(Xn) and autocorrelation coefficients of the influence factors r(X1), ..., r(Xn), the specific energy consumption E is measured. The stationary energy consumption precedent fixed in this way is transferred to the central computer for further processing.

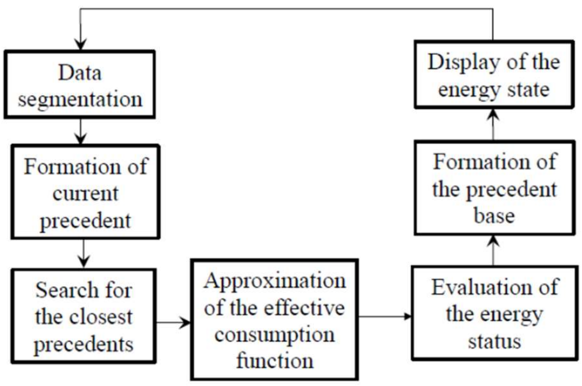

Figure 5. Scheme of the energy consumption monitoring cycle.

At the second stage of the monitoring cycle, the closest neighbors to the recorded current precedent are searched in the database of precedents [17]. It is assumed that all precedents are located in the space of mathematical expectations of influencing factors. The search for nearest neighbors to the current precedent is performed according to the formula for calculating distances in the Euclidean space of mathematical expectations of influencing factors:

$$dM_{ij}(X) = \sqrt{\sum_{k=1}^{n}(M_i(X_k) - M_j(X_k))^2},$$

where $dM_{ij}(X)$ is the distance between the influence factors of the i-th current precedent and the j-th precedent from the precedent base. Thus, there are n precedents in the precedent database that are the closest neighbors to the current precedent. At the third stage of the monitoring cycle, the dependence of the consumed energy on the influencing factors is approximated based on the data of the nearest precedents using the method of least squares [18]. The obtained function characterizes the dependence of already achieved levels of effective energy consumption on technological parameters. By substituting the values of the technological parameters of the current precedent into it, we obtain the estimated value of effective energy consumption for the current precedent.

At the fourth stage of the monitoring cycle, the presence of hidden energy losses is determined. For this, the difference between the energy consumption of the current precedent and the effective energy consumption obtained by the calculation method at the previous stage is calculated. Depending on the result of the comparison, we draw a conclusion about the energy efficiency of the equipment being monitored. If the difference is equal to or less than zero, it is considered that the equipment is working efficiently, and the current precedent refers to the precedents of efficient energy consumption. If the difference is greater than zero, it is considered that the equipment works with hidden energy losses [19].

At the fifth stage of the monitoring cycle, the database of precedents is filled with new recorded precedents. At the same time, precedents automatically replenish the database of precedents only if the equipment is working efficiently. In all other cases, the person making the decision is provided with a message describing the current situation to make a final decision related to the search for the causes of energy losses.

IX. COMPARISON OF METHODS

Numerical modeling of precedent energy monitoring was performed on the data of chemical production given in [21]. The volumes of produced ammonia and consumed natural gas are accepted as factors influencing electricity consumption. The consumed electricity calculated according to the regression and precedent model is compared. The simulation results are shown in Table 1.

Table 1. Comparison of regression and precedent approaches.

Produced ammonia, tone	Used natural gas, 1000 m^3/hour	Actually used electricity, 1000 kWh	Used electricity according to the regression model, 1000 kWh	Used electricity according to the precedent model, 1000 kWh
39,699	45,211	31,988	31,988	31,959
39,292	45,182	32,005	32,066	31,608
39,644	45,357	31,932	31,966	32,055
39,929	45,122	31,923	32,038	31,934
39,684	45,481	32,105	32,191	32,003
39,967	45,782	32,056	32,164	32,499
39,422	45,761	32,063	32,251	32,123
43,174	45,602	32,098	32,05	31,873
42,055	45,608	31,971	33,247	32,178
40,449	45,023	31,953	32,79	31,842
41,385	44,973	31,86	32,27	31,922
46,907	53,037	35,576	35,576	35,551
46,923	52,979	35,532	35,699	35,565
46,109	52,78	35,521	35,67	35,594
46,772	52,693	35,491	35,395	35,508
46,583	52,644	35,501	35,598	35,446
46,821	52,893	35,538	35,581	35,565
46,865	52,657	35,504	35,616	35,469

When building a precedent model, 18 precedents were considered. For each of the precedents, 4 nearest neighbors were selected, on which, by the method of least squares, the linear function of efficient energy consumption was built and the efficient energy consumption was calculated.

Fig. 6 provides simulation results in a more convenient graphical form. It clearly demonstrates that the results of the automated determination of the function of effective energy consumption using machine learning precedent – analytical method gives results no worse than the traditional regression method.

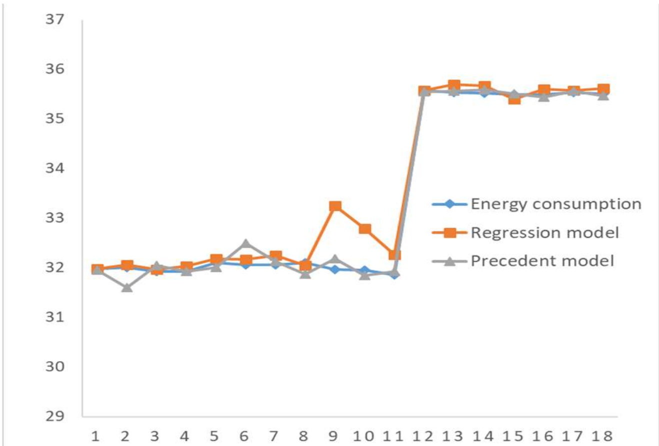

Figure 6. Comparison of the results of regression and precedent-analytical modeling.

X. CONCLUSIONS

The analysis of related literature demonstrates the need to extend energy efficiency monitoring to the level of individual, specific technological systems. This problem can be solved by intellectualizing the processing of technological parameters.

In this paper, it is proposed to apply the method of analysis of precedents of stationary energy consumption to assess energy losses in each technological system of the enterprise.

The precedents of stationary energy consumption include mathematical expectations of technological parameters recorded at stationary sites and the corresponding values of energy consumption.

The evaluation of energy losses is based on real-time comparison of the actual current energy consumption of the technological system with the estimated value, which is taken as consumption with allowable losses.

The calculation of the value of energy consumption with allowable losses is performed by grouping close precedents and constructing a linear regression of efficient energy consumption on the technological parameters accumulated in the precedents.

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