Chapter

Estimation of Hidden Energy Losses

Borys Pleskach

Abstract

Most industrial or municipal energy consumers involve the conversion of electricity, either into useful products or into other types of energy. For example, lighting systems, heating systems, air or water supply systems. And in all such systems there are energy losses, which can be divided into open, or technological and hidden, or abnormal. Open losses are inherent in the technological process itself and depend on the principle of energy conversion, flow conditions, the type of equipment received, and so on. Hidden losses in the technological system occur accidentally due to the appearance of defects in the equipment, erroneous actions of personnel, changes in uncontrolled external conditions. The paper considers a method of detecting and estimating hidden energy losses, based on the analysis of energy consumption precedents and building a decision support system aimed at eliminating such energy losses. Models of energy consumption precedents are formed on the basis of controlled technological parameters and their statistical estimates. In the future, local standards of efficient energy consumption are formed from individual precedents. The advantage of this method of estimating latent energy losses is the adaptation of standards of efficient energy consumption to the conditions of the consumer.

Keywords: Energy losses, energy efficiency, energy saving, precedent analysis, energy consumers

1. Introduction

The increase in the cost of energy and their availability, as well as the growing impact of energy-consuming technological systems on the environment, require the introduction of systematic measures aimed at improving the energy efficiency of production. At the same time, it is predicted [1] that energy consumption will increase in the future. This will especially affect electricity. Worldwide, about 50% of total electricity consumption is carried out in industry by conversion using electric motor systems [2]. The highly automated industry of developed countries converts almost 60-75% of all electricity distributed in four types of electric motor systems into mechanical movement of about 40%, of which compressors 25%, pumps 20% and fans 15%. This study shows that the control system, based on the analysis of technological parameters and intensity of electricity consumption from electric motor systems, can be widely used in industry [3].

The gradual transition from traditional to renewable energy sources requires an improvement in the balance of supply and demand, the creation of active energy consumers capable of controlling their own energy efficiency and maintaining their own energy sources. Eliminating hidden energy losses in both energy consumption and generation gives businesses additional benefits.

Improving the energy efficiency of consumers in industry was mainly achieved through the introduction of new technologies, new more economical equipment, construction using new energy-saving materials, heat recovery, and so on. To a lesser extent, organizational approaches to energy consumption management were introduced, i.e. planning and production management taking into account the economically feasible use of energy resources. This is due to the fact that organizational approaches are closely integrated into production planning and control systems, and require additional investment costs for the development of information technology aimed at energy saving. Obtaining information on energy consumption and linking it to operational information to get an idea of the behavior of equipment and technological systems has proven to be technically difficult. However, the potential for energy savings from organizational approaches is quite significant [4]. Energy management combines the overall management of the enterprise with the needs of improving the energy efficiency of technological systems.

This work is aimed at the study of operational monitoring and analysis of energy consumption as a sequence of cases of stationary and quasi-stationary energy consumption. With regard to energy saving, real-time information can raise awareness of employees of the presence of hidden energy losses and influence their actions. Operational monitoring of deviations of energy consumption from the accepted values of efficient energy consumption can be an indicator of equipment performance and a tool to support maintenance measures. Specific equipment failures can be predicted by identifying certain patterns of energy consumption. Responding quickly to such events can prevent catastrophic equipment failures. Thus, energy monitoring becomes a driver of equipment reliability, technological process stability and product quality.

2. Purpose of work

Most energy consumers convert the received energy and raw materials into a useful product. Technological equipment, production products and performers are involved in this transformation process. Each of these links can affect energy consumption and energy losses. The specific energy consumption of the technological system E is characterized by the vector of influential technological parameters $X = \{x_1, x_2, \dots, x_k\}$ and a set of random uncontrolled factors Z that cause hidden energy losses ΔE.

$$E = f(X, Z) = \varphi(X) + \Delta E \tag{1}$$

Hidden energy losses from the consumer can be caused by violations of the technical condition of the equipment, deterioration of the properties of raw materials, erroneous actions of personnel, and other factors that are usually not subject to automated control. The problem is to provide real-time staff with information on the presence and extent of hidden energy losses in each technological system of the enterprise, based solely on influential technological parameters and specific energy consumption. The purpose of this work is to develop methods for estimating latent energy losses based on the analysis of cases of quasi-stationary energy consumption.

3. Known methods of monitoring energy losses

Energy efficiency of the consumer is determined by the ratio of the amount of energy consumed to the amount of product received, or services provided when working in a certain mode. In the absence of energy losses, this figure will take the minimum values in all modes of operation. When energy losses occur, it will increase. At the same time, the performance of the technological system depends on the parameters that determine its mode of operation, and accordingly on the intensity of energy consumption.

The dependence of energy consumption on the set of technological parameters X in the absence of random uncontrolled factors Z will be called the function of efficient energy consumption, and the value of this function at certain technological parameters X - efficient energy consumption E_{ef}. That is, energy consumption without hidden energy losses:

$$\mathrm{E_{ef}} = \varphi\,(\mathrm{X}) = \mathrm{f}\,(\mathrm{X}, \mathrm{Z} = 0) \tag{2}$$

Energy efficiency monitoring and, accordingly, the estimation of latent energy losses are based on the comparison of the current energy consumption E with the efficient energy consumption E_{ef} obtained from Eq. (2).

$$\Delta \mathrm{E} = \mathrm{E} – \mathrm{E_{ef}} \tag{3}$$

The function of efficient energy consumption, and consequently the value of efficient energy consumption, at certain technological parameters, is usually determined in several ways. There is a method when efficient energy consumption is obtained by calculating the known empirical or analytical dependences of electrical engineering, heat engineering, mechanics, hydraulics [5]. This method gives an approximate estimate of the reference energy in the real technological process. Another way to obtain an estimate of efficient energy consumption is based on testing tests of equipment and determining the normative energy consumption when operating equipment under specified conditions [6]. Such estimates of regulatory energy consumption do not always correspond to effective standards in real production [7]. There is also a method when energy efficiency is considered to be achieved a certain period of time ago, when the technological parameters were similar. 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 [8] for comparison with current energy consumption.

4. Assessment of hidden energy losses

The paper proposes to use the methods of precedent analysis [9], based on cases of efficient energy consumption, to evaluate and monitor the standards of efficient energy consumption. To do this, each energy consumer in the production process must be equipped with a system of sensors of influential technological parameters associated with a programmable controller of the monitoring system, whose task is to recognize the precedents of quasi-stationary energy consumption.

The precedent of quasi-stationary energy consumption *CaseE* will be the case in which all normalized influential technological parameters $X = \{X_1, X_2, \dots, X_n\}$ for a certain period of time remain within predetermined allowable values $\pm \Delta x_n = \sigma$. The precedent has the following structure:

$$CaseE = \left\langle \begin{array}{ccc} M(X_1), & \dots, & M(X_n); \\ D(X_1), & \dots, & D(X_n); \\ r(X_1), & \dots, & r(X_n); \\ E, & \tau, & S \end{array} \right\rangle \tag{4}$$

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

$D(X_1), \ldots, D(X_n)$ - statistical variance of influencing factors $X_1, \ldots, X_n$;

$r(X_1), \ldots, r(X_n)$ - autocorrelation coefficients of influencing factors $X_1, \ldots, X_n$;

n - is the number of interdependent influential technological parameters;

E - specific energy consumption for the period of quasi-stationary state;

τ - duration of steady state;

S - probable diagnosis of technical condition.

The precedents obtained in this way form in the n-dimensional space of influential technological parameters $\{X_1, X_2, \ldots, X_n\}$ a cloud of precedents of quasi-stationary states of the technological system with different estimates of energy consumption. In this cloud, precedents with minimal energy consumption form the surface of cases of efficient energy consumption.

$$E_{ef} = \varphi(X_1, X_2, \ldots, X_n) = f(X, Z = 0) \tag{5}$$

The estimation of latent energy losses in an arbitrary i-th case (E_i) is based on the determination of a local standard of efficient energy consumption for the i-th precedent. To do this, from the base of precedents of efficient consumption is selected n precedents closest to the current precedent and on them, by the method of least squares, calculate the regression coefficients $b_0, b_1, b_2, \ldots, b_n$ – the function of efficient energy consumption for the current precedent. The value of effective consumption for the current i-th precedent is calculated by the formula:

$$E_{efi} = b_0 + b_1 M(X_{1i}) + b_2 M(X_{2i}) + \ldots + b_n M(X_{ni}) \tag{6}$$

After that, the difference between the obtained value of E_{efi} and the current specific energy consumption E_i is calculated: $\Delta E_i = E_{efi} - E_i$. Depending on the obtained value of ΔE_i it is possible to draw a conclusion about the energy efficiency of the equipment that is subject to monitoring. If $\Delta E_i \approx 0$, the equipment is considered to be operating efficiently, if $\Delta E_i > 0$, the equipment is operating with reduced energy consumption and energy savings are equal to ΔE_i, if $\Delta E_i < 0$, the equipment is operating with energy losses up to ΔE_i.

5. Information support for monitoring hidden energy losses

The flow of derived data from the sensors enters the monitoring system in the form of a time series. The difficulty lies in the synchronization and subsequent search for the relationship between the vector of technological parameters and the intensity of energy costs. This complexity can be overcome by segmenting the time series and allocating stationary areas from its composition, which will be considered as precedents for energy consumption. An overview of possible methods of time series segmentation is given in [10].

Time series $T = \{(X_1, E_1); (X_2, E_2); \ldots, (X_m, E_m)\}; 1 \le m \le M$ is a finite set of M n-dimensional structured sequences of regime parameters $X = [x_1, x_2, \ldots, x_n]$ and the corresponding energy consumption intensity E, marked by timestamps $t_1, \ldots, t_M$. Segmentation of the time series T divides it into a sequence of independent series $T = \{S_1, S_2, \ldots, S_i\}$ that do not overlap. The segment S of the time series T is a finite set of structured elements (X_m, E_m) marked with timestamps $t_a, \ldots, t_n, \ldots, t_b$: $S_i = \{(X_a\ E_a); \ldots; (X_b, E_b)\}$.

The purpose of the procedure of segmentation of the time series of mode parameters is to divide the data flow into separate disparate areas with similar characteristics and to allocate among them areas with signs of stationarity [11]. To formalize the relationship between the elements of the series, a special function of the price of entry into the segment *Cost{S}* is introduced, which determines the relationship between the elements of the series. Usually the function of distance between elements of a series or groups of elements is used for segmentation [12, 13]. In this paper, for time series segmentation, it is proposed to use the function of the distance d between the elements X_1 and X_i of the time series in the n-dimensional Euclidean space of mode parameters X:

$$Cost\{S\} = d(X_1, X_i) = \sqrt{(x_{11} - x_{1i})^2 + (x_{21} - x_{2i})^2 + \cdots + (x_{k1} - x_{ki})^2} \tag{7}$$

The condition of inclusion of the next, i-th, group of the received mode parameters X_i, E_i to the next segment S, which is filled with data:

$$Cost\{S\} = d(X_1, X_i) \leq \sigma \tag{8}$$

where: σ is a threshold value that is determined empirically.

The pseudocode of the algorithm segmentation of the time series of determining mode parameters is as follows:

- open a time series segment;
- get and save in the open segment the first set of mode parameters X_1, E_1;
- obtain the next set of mode parameters X_i, E_i and calculate the entry price of this set in the open segment according to formula (7).
- as long as the segment entry price for the new sets of mode parameters is less than the threshold value σ, according to formula (8), they join the open segment. Otherwise, the open segment is closed and passed for further processing, a new segment is opened and it is the first to enter a set of mode parameters for which the entry price was higher than the threshold value. And then the cycle repeats.

The algorithm in the pace of the technological process processes the derivative flow of mode parameters, determines the segments with signs of stationarity and transmits them for further processing to calculate the hidden energy losses. The procedure of segmentation of the flow of mode parameters of the technological system can be implemented in a separate programmable controller located in the area of energy metering.

6. Formation of a base of precedents

During the assessment of latent or abnormal energy losses in the composition of the upper-level computing device, a base of precedents of quasi-stationary consumption is formed. The initial filling of the precedent database is performed with the participation of an expert. Let *Case* be a set of precedents. It is believed that all precedents of energy consumption are located in an unlimited space of mathematical expectations of regime factors. In this space the function of distance between precedents is set:

$$\mathrm{d}(\mathrm{Casei\ Casej}) = \sqrt{\sum \left(M(X_{ni}) - M\left(X_{nj}\right)\right)^2} \tag{9}$$

Considerations based on the analysis of precedents are to search among all recorded precedents of the nearest neighbors to the current one and to build a linear approximation of the function of efficient energy consumption in the nearest neighbors. The search for the nearest neighbors is carried out among a large number of precedents. To simplify this procedure, it is proposed to involve a clustering mechanism. Clustering of precedents is the process of combining precedents into groups characterized by similar features. Unlike the usual classification, where the number of groups of objects is fixed and predetermined by a set of precedents, here neither groups nor their number are predetermined and formed in the process of the system, based on a certain degree of proximity of precedents [14, 15].

The formed clusters represent separate disjoint areas of function (2). It can be assumed that the precedents assigned to the same cluster belong to one area of the energy efficiency function. These clusters, in turn, are proposed to be used as a basis for determining the proximity of precedents. Suppose that we gradually obtain a sequence of precedents of static energy consumption. It is necessary to assign each of them to one of the disjoint subsets at the rate of obtaining precedents so that each cluster consists of precedents, which according to the metric $d(Case_i\ Case_j)$ were in the area of existence of the cluster. In this case, each precedent is assigned the identifier of the cluster $n \in N$, to which it belongs. We assume that the space of mathematical expectations of influencing factors has zero precedent Case_0 with zero values of influencing factors. The distance from the zero precedent to any other precedent is determined by the dependence:

$$d(Case_0, Case_i) = \sqrt{\left(M_i(X_1)^2 + M_i(X_2)^2 + \cdots + M_i(X_n)^2\right)} \tag{10}$$

Each of the clusters is characterized by an initial radius R_i and a depth of existence ΔR. The initial radius of the cluster is the distance between the zero precedent of Case_0 and the nearest cluster boundary (**Figure 1**) $R_i = d\ (Case_0, Case_i)$. The area of existence of the cluster is a set of $Case_i$ precedents (marked with asterisks in the figure) that satisfy the condition $R_i \le d\ (Case_0, Case_i,) < R_i + \Delta R$.

The clustering algorithm is a function a: $Case_i \to n$ which matches the cluster identifier $n \in N$ to any precedent, and the set N is unknown in advance. As the

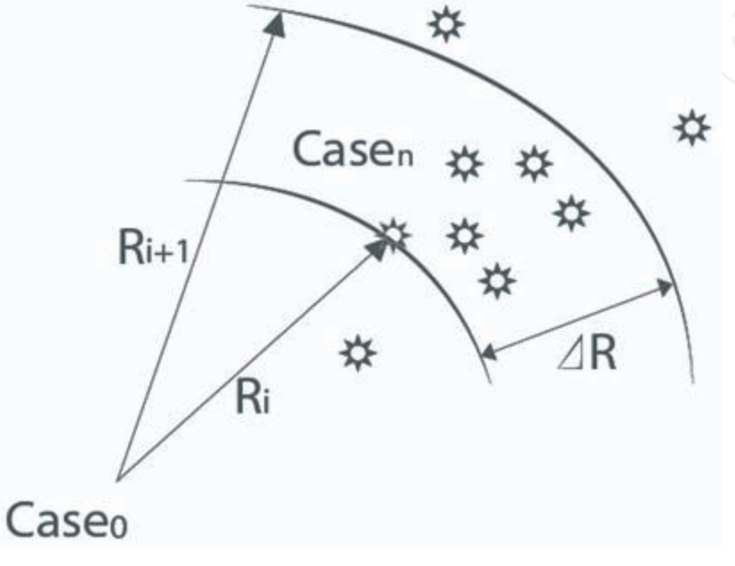

Figure 1.
Cluster diagram.

identifier n of the cluster, it is advisable to use its radius, which is calculated by the formula:

$$n_i = R_i = \left\lfloor \frac{d\left(Case_0\, Case_j\right)}{\Delta R} \right\rfloor \tag{11}$$

In the future, we look for the nearest neighbors only among the precedents of the current cluster. New precedents are placed in the base of effective precedents only in the absence of energy losses (see **Figure 2**).

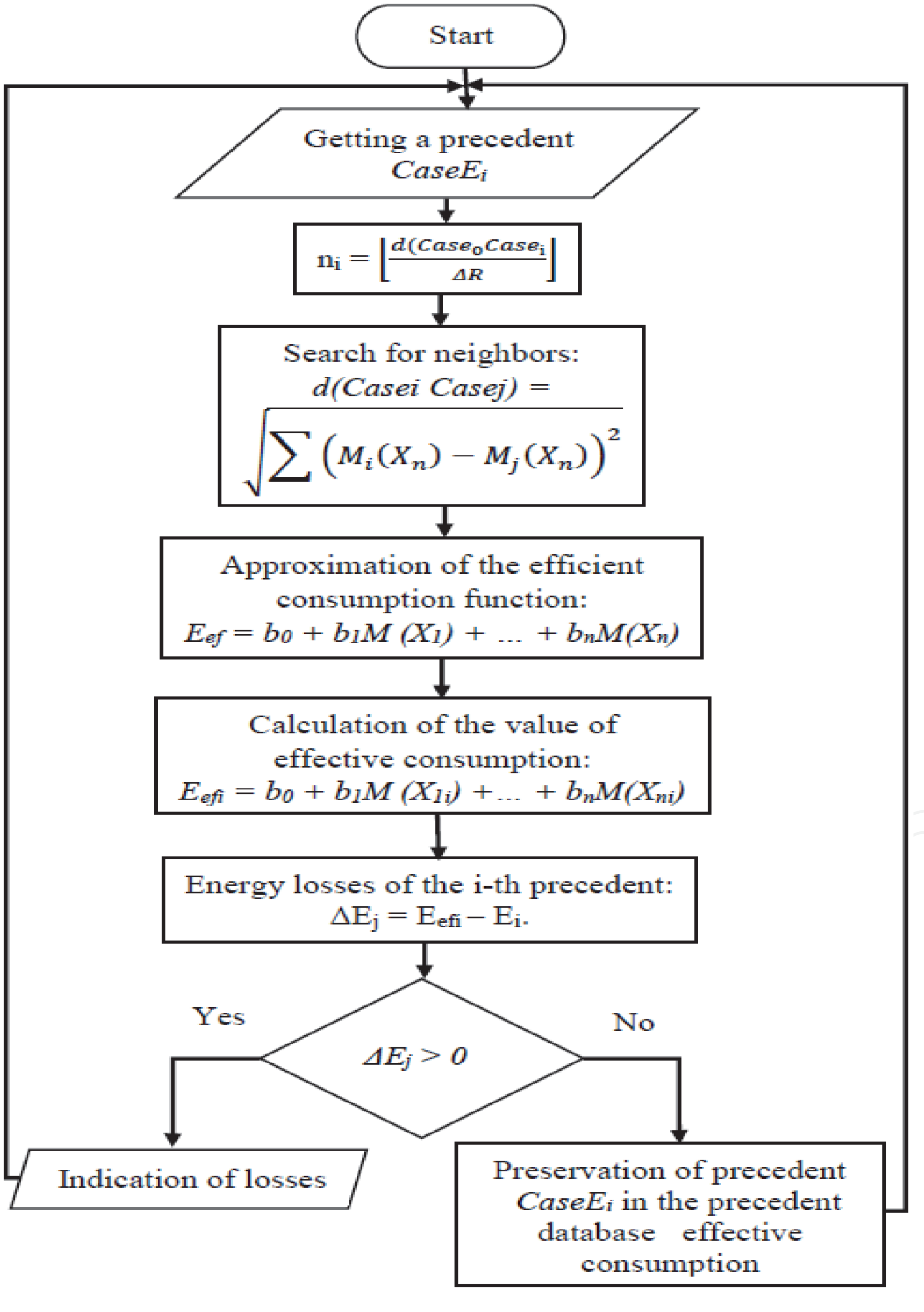

Figure 2.
Cyclic algorithm for forming a base of precedents and determining the amount of power of efficient energy consumption.

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

Table 1.
Comparison of regression and precedent approaches.

Numerical modeling of the method of precedent estimation of energy losses was performed on the data of chemical production given in [16]. The volumes of produced ammonia and consumed natural gas are accepted as factors influencing electricity consumption. The actual consumed electricity calculated according to the regression and precedent model is compared. The simulation results are shown in **Table 1**.

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.

7. Conclusion

This chapter proposes a method for detecting and estimating latent and abnormal energy losses in production technology systems. The methodology is based on a retrospective analysis of cases of quasi-stationary energy consumption.

Author details

Borys Pleskach
Department of Energy Saving, Pukhov Institute for Modelling in Energy Engineering, Kyiv, Ukraine

*Address all correspondence to: bn.pleskach@gmail.com

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