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ASSEMBLY TIME STANDARD SETTING BASED ON KERNEL ESTIMATORS

Time standards belong to vital indicators of the production process that facilitate making decisions related to product and process improvement. The presented issues concern the determination of the assembly time standard using kernel estimators. The development of neural networks offers the possibility to identify begin-end points in the assembly process that can provide big data related to the assembly time standard. The problem addressed in this paper is development of a method of big data analysis, on the basis of which the assembly time standard can be determined. In the presented approach adequate formulas are developed together with some examples. The paper presents an application of the theory of kernel estimators as well as results of the proposed approach.

1. INTRODUCTION

In industrial engineering, standard time is the time required to perform a specified task [1]. The term work system, which includes aim, input, output, employee, workstation, work method, and environment, allows us to accurately characterise the task for which the time standard is determined.

The techniques used to determine standard time include, among others: [2]: time study, predetermined motion time system, standard data system, and work sampling. However, they are time consuming and do not benefit from the application of artificial intelligence.

Standard time is the product of three factors [1,3]:

1. Observed time: the time measured to complete the task.
2. Performance rating factor: the number reflects the pace the person is working at; 90% is working slower than normal, 110% is working faster than normal, 100% is normal. This factor is calculated by an experienced worker who is trained to observe and determine the rating.
3. Personal, fatigue, and delay (PFD) allowance.

Standard time can be calculated using formulas (1) and (2) [3].

$$t_n = t_{obs} \bullet (PR) \tag{1}$$

$$t_{std} = t_n \bullet (1+A_{pdf}) \tag{2}$$

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Where:
t_n– normal time,
t_{obs}– observed time,
PR– performance rating,
t_{std} – standard time,
A_{pdf}– personal fatigue delay (PFD) allowance.Time standards in industrial engineering are useful for a number of processes, including [1, 3] workforce planning, line balancing, simulation, improvement and optimisation, cost accounting, or employee evaluation.

Monitoring and simulation of production processes are key methods for their improvement and optimization. Modern mathematical methods provide new opportunities for acquiring and analysing data from production processes. Time studies are time-consuming and may not cover all work tasks. Therefore, it is necessary to look for methods that give good results in terms of reliability and accuracy and take advantage of the opportunities offered by artificial intelligence.

The aim of the study is to develop a time standard setting method based on big data with the use of kernel estimators.

The scope of the issues presented in the article includes, in the second section, an analysis of the assembly process presenting the classification of assembly due to the level of automation and the main achievements related to the application of artificial intelligence methods in the area of assembly. The next section presents an overview of methods for determining time standards. The fourth section describes the proposed approach, the fifth section presents examples of its application, and the final section focuses on conclusions.

2. ASSEMBLY PROCESS ANALYSIS

Assembly systems include manual assembly, semi-automatic assembly, adaptive assembly, automatic assembly, and flexible assembly [5]. Manual assembly involves composing previously manufactured components and/or sub-assemblies into a complete product or unit of a product, primarily performed by human operators using their inherent dexterity, skill and judgment. Manual assembly can be further assisted by mechanized or automated systems for feeding, handling, fitting and checking operations [6]. Mital et al. [7] have developed design guidelines for automatic assembly. Researchers such as Poli have presented a set of qualitative guidelines on design for assembly (DFA) [8] to recognize these features of a part which affect manual assembly time, and thereby the cost. Manual assembly time depends on numerous features. A widely studied aspect of assembly is the analysis of human movements. Gesture recognition was analysed by Qu et al. [9], whereas leg movement was analysed by Shi et al. [10].

Many authors [11-14] apply artificial intelligence (AI) in their research. For example, machine learning is used for prediction in maintenance. It is also used in additive manufacturing and bioprinting, and kernel estimators are applied for work process analysis. Kernel estimators are one of the promising methods for analysing big data sets [15-21].

Need to look for new methods to determine the time standard of assembly operations stems from:

- development of computational tools for obtaining feedback on design manufacturability and process selection to connect designers with manufacturers [22];
- continuous development of human-centric, resilient, and sustainable manufacturing towards Industry 5.0, Artificial Intelligence (AI) has gradually unveiled new opportunities for additional functionalities, new features, and tendencies in the industrial landscape; [23];
- manual assembly process of complex products is lengthy, the assembly requirements are difficult to recall, and the assembly quality requirements are high [24];
- ongoing transformation of the manufacturing sector towards Industry 4.0 is driven by the increasing importance of new technologies, such as Virtual Reality (VR) and Digital Twins (DTs). VR enables immersive and interactive experiences, while DTs facilitate real-time monitoring and control of manufacturing systems [25];
- assembly sequences affect the results of assembly feasibility. Assembly sequence also impacts assembly costs, such as cycle time. In some extreme cases, the improper sequence may leave no space for a robot to accomplish a specific remaining task. Sequence may be optimized to improve assembly efficiency [26];
- as an emerging manufacturing paradigm, Industry 5.0 emphasizes human-centric intelligent manufacturing. XR technology (a general term of virtual reality, augmented reality and mixed reality) brings unprecedented opportunities for assembly in such manufacturing paradigm [27];
- need for the implementation of flexible and reconfigurable production systems, that are capable of producing highly customized products of different production sizes [28];
- the global automobile manufacturing industry is under pressure due to highly customizing customer expectations. The industry is seeking new and applicable policies to overwhelm such challenges. Even though top managers still have remained hesitant, digital transformation and emerging technologies are considered new opportunities for many executives in the automotive industry [29];
- quality prediction holds significant importance in monitoring the operational status of industrial systems [30].

3. TIME STUDY

Time standards can result from measurements of industrial processes or from predictions (Fig. 1). An important method of setting time standards is the time study. Time study is a direct and continuous observation of a task to record the time taken to accomplish the task [1].

The proposed approach applies artificial intelligence to capture and analyse the data related to manufacturing and standard time setting.

A time study requires an experienced person to be able to set the performance rating factor. Therefore, different people can set the performance rating factor at different levels.

Artificial intelligence offers the ability to capture and analyse big data sets. The presented approach uses kernel estimators, which are a non-parametric method for estimating the probability density function of a given variable.

Setting a time standard requires analysing the production process and separate tasks for which the time standard is to be set. For this purpose, a deep neural network can be used to effectively identify the begin-end point of production tasks [4]. Hence, it is possible to capture the big data from the production process. The time data analysis can be supported by kernel estimators.

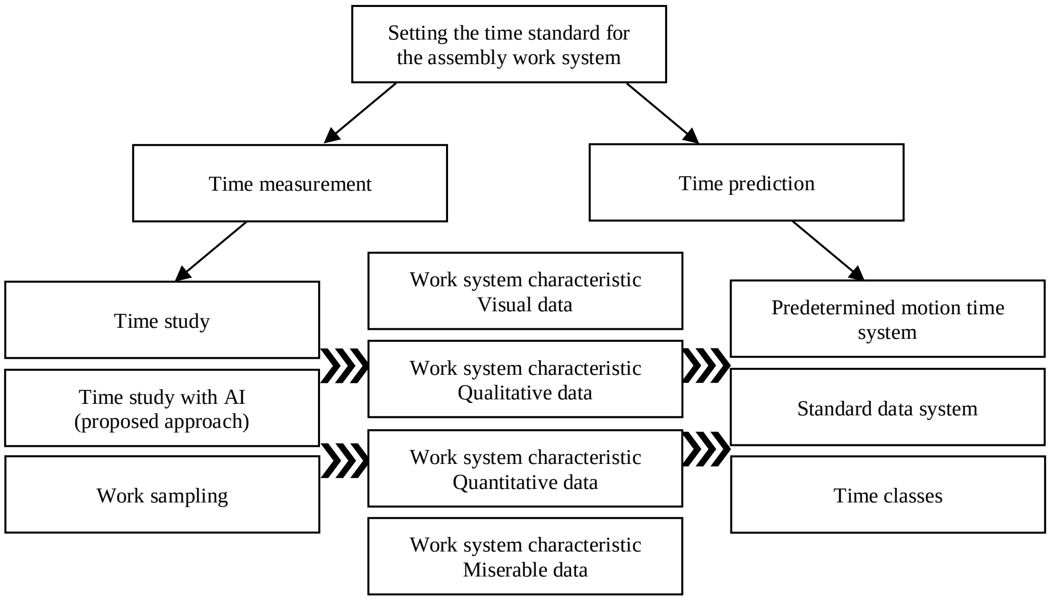


Fig. 1. Time standard setting methods

The article presents a method for analysing data modelled by kernel estimators for determining time standards, avoiding performance rating factor which is difficult to fix (Fig. 2). The overview of the proposed approach is shown in Fig. 3.

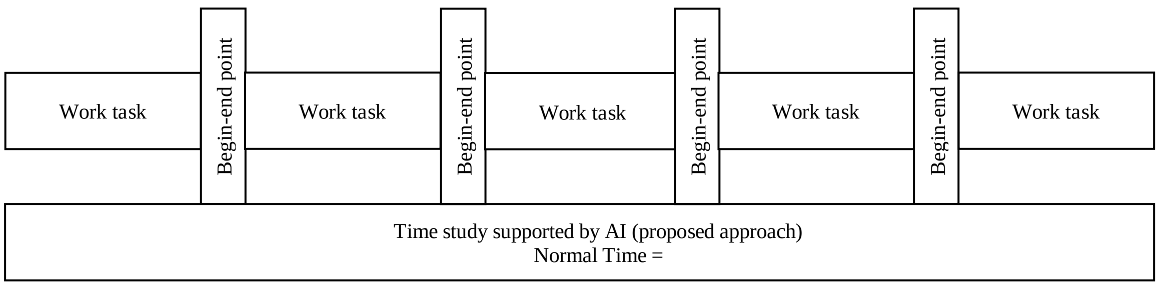


Fig. 2. Normal time setting

Time study procedure consists of the following steps [1, 2, 15]:

1. Setting the research goal. The goal of the study defines the scope and detail of the analysis of the work process, as well as the required accuracy of the results obtained.
2. Experimental design. Defining and documenting the standard method. Dividing the task into work elements. Preparation of study, which includes activities such as determining the way of documenting the measurements and selection of measuring instruments. Description of the work process performed on the workstation, which includes separating the activities carried out, determining their repetitiveness in the

production cycle and factors that influence the labour intensity of the performed activities. Determining the number of necessary measurements which, among others, influence the accuracy of the obtained measurement results.

3. Timing the work elements to order to obtain the observed time for the task. Collecting time data using a timekeeping device (e.g., decimal minute stopwatch, computer-assisted electronic stopwatch, and videotape camera). Evaluate the worker's pace in relation to standard performance (performance rating), to determine the normal time.
4. Data analysis. Determine the time of separate activities and the accuracy of the obtained measurement results. Apply an allowance to the normal time to compute the standard time. The allowance factors that are needed in the work are then added to compute the standard time for the task.
5. Reporting.

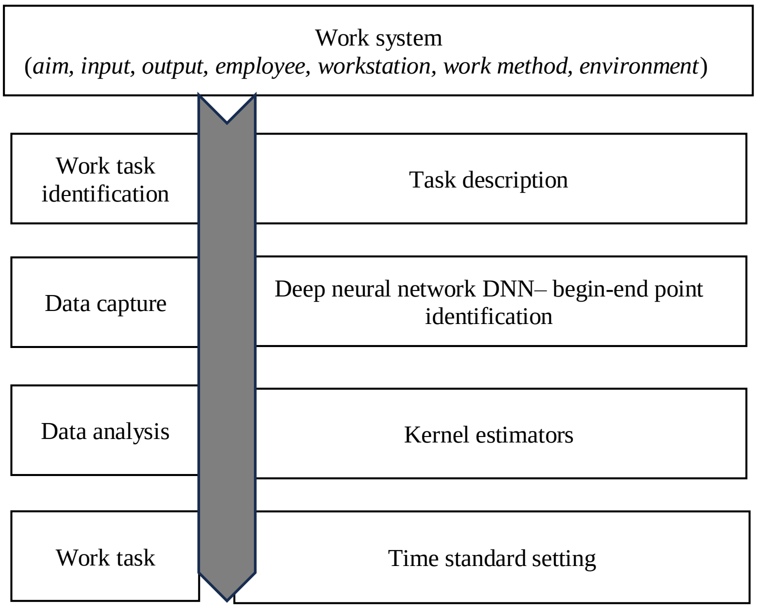


Fig. 3. Overview of the proposed approach

The normal time can be determined from the following equation: [15]

$$t_n = \frac{PR}{100}\,\bar{t} \tag{3}$$

Where:
t_n – normal time,
PR – performance rating factor expressed in %,
$\bar{t}$ – average time of the tasks.

Each extracted action requires the determination of the accuracy of the obtained measurement results e, which can be calculated from formula (4) [15].

$$e = \frac{B \cdot s}{\bar{t}} \tag{4}$$

Where:
s – standard deviation,

B – stabled factor, see [15],
$\bar{t}$ – average time of tasks,
e – accuracy of the obtained results expressed in %,
Data should be collected based on the same work system characteristic.

4. THE PROPOSED APPROACH FOR TIME STANDARD SETTING

4.1. KERNEL ESTIMATORS

Kernel density estimation (KDE) is the application of kernel smoothing for probability density estimation. KDE answers a fundamental data smoothing problem where inferences about the population are made based on a finite data sample [16–18].

Kernel density estimator [19, 20] is a type of a non-parametric estimator designed to determine the density of the distribution of a random variable, based on the values that the variable under study has taken during measurements. This method can be used to analyse data in the field of manufacturing engineering, among others.

The kernel density estimator method involves the estimation of empirical distributions by means of a known density function of the kernel estimator averaging successively the values of the variable under study. The probability density kernel estimator can be determined from equation (5) [19–21].

$$\hat{f}(x|h) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x-x_i}{h}) \tag{5}$$

Where:
x_i – individual elements of an n-element random sample,
x – averaged elements,
$K(\cdot)$ – kernel,
h – positive number, called bandwidth or smoothing factor.

The kernel K can take different forms. The normal kernel K is defined by equation (6) [20].

$$\mathrm{K(x)} = \frac{1}{\sqrt{2\pi}}\mathrm{e}^{-\frac{x^2}{2}} \tag{6}$$

The Epanechnikov kernel is defined by equation (7) [20].

$$K(x) = \begin{cases} \frac{3}{4}(1-x^2) & for \quad x \in [-1,1] \\ 0 & for \ x \in (-\infty,-1) \cup (1,\infty) \end{cases} \tag{7}$$

The unitary kernel is defined by equation (8) [20].

$$K(x) = \begin{cases} \frac{1}{2} & for \quad x \in [-1,1] \\ 0 & for \ x \in (-\infty,-1) \cup (1,\infty) \end{cases} \tag{8}$$

The two-weight kernel is defined by equation (9) [20].

$$K(x) = \begin{cases} \frac{15}{16}(1-x^2)^2 & for \quad x \in [-1,1] \\ 0 & for\, x \in (-\infty,-1) \cup (1,\infty) \end{cases} \tag{9}$$

The triangular kernel is defined by equation (10) [20].

$$K(x) = \begin{cases} 1-|x| & for \quad x \in [-1,1] \\ 0 & for\, x \in (-\infty,-1) \cup (1,\infty) \end{cases} \tag{10}$$

The choice of kernel form depends on the nature of the data [21].

4.2. TIME STANDARD SETTING WITH KERNEL ESTIMATORS

The analysis of the production process can be performed, for example, through visual identification of begin-end points, which allows big data to be acquired. The proposed procedure algorithm for production process analysis is shown in Figure 4.

The algorithm uses a kernel density estimator for process evaluation. The graphical presentation of the results makes it possible to assess the repeatability of the tasks in the production process.

In the proposed algorithm, the first step is to analyse the process by identifying the tasks in the process and identifying the begin-end points, which can be conducted, for example, visually. In a production process, some activities are carried out in each work cycle, whereas others are carried out at intervals. Using the classic time study method, it might occur that activities carried out from time to time are omitted from the analysis. Therefore, the use of automatic process analysis will allow these activities to be identified and analysed.

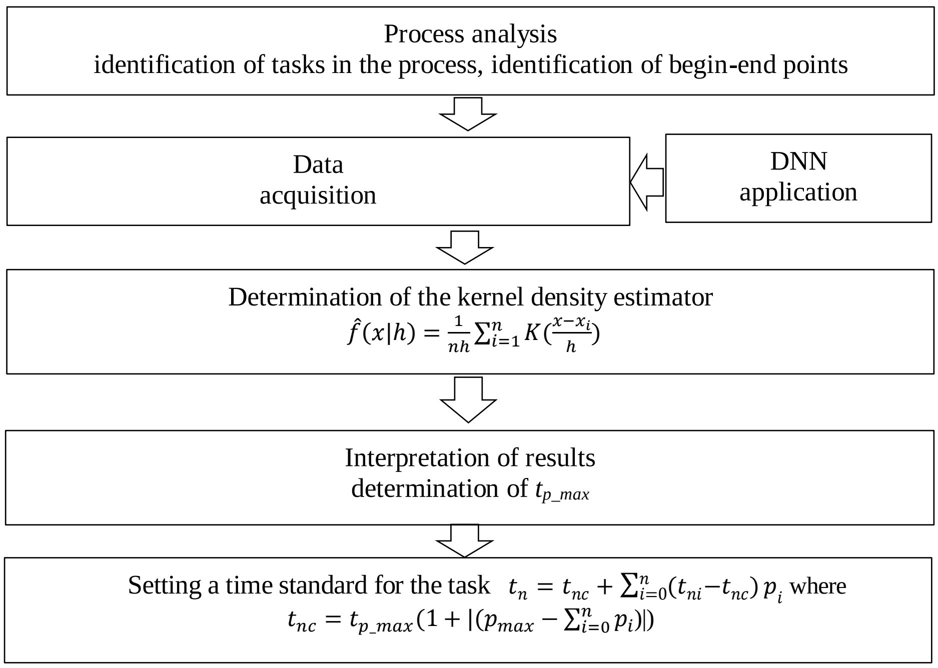


Fig. 4: The proposed algorithm for data analysis

The next step of the proposed method is to determine the time of the extracted tasks. The automatic time determination method is not the subject of this article.

The following step is determination of the density kernel estimator, which allows to identify the activities that are performed regularly and these that are performed periodically. The extremes illustrate activities that are performed repetitively, while disturbances are illustrated by the ‘tails’ in the right-hand part of the graph.

Standard time is focused on given work system, which included:

- aim – task to do,
- input – materials, information, energy,
- output – component processed,
- person – skills, personality,
- workstation and tools,
- work method,
- environment – temperature, humidity, air flow.

In the proposed approach normal time is calculated according to the formula (11).

$$t_n = t_{nc} + \sum_{i=0}^{n}(t_{ni} - t_{nc})\, p_i \tag{11}$$

$$t_{nc} = t_{p\_max}(1 + |(p_{max} - \sum_{i=0}^{n} p_i)|) \tag{12}$$

Where:

t_{nc} – productive work time of the cyclically repeated activity (each cycle),
t_{p_max} – time value for the global extremum of the kernel density estimator,
p_{max} – probability for the global (maximum) extremum of the kernel density estimator,
p_i – probability of local extremes,
t_{ni} – work time of a periodic activity (every certain number of cycles),
t_n – normal time of a technological operation.

A comparison of the proposed approach with the time study is shown in Table 1.

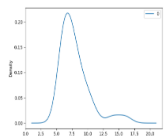
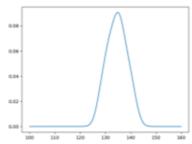
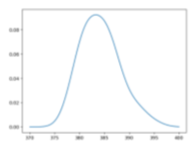
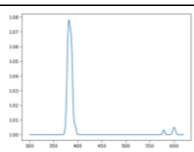
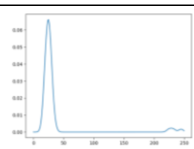
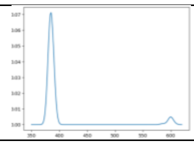
Table 1. Comparison of methods

No	Proposed approach	Conventional method based on time study
1	Normal time calculation method $t_n = t_{nc} + \sum_{i=0}^{n}(t_{ni} - t_{nc})\, p_i$	Normal time calculation method $t_n = \frac{\text{PR}}{100}\bar{t}$
2	Standard time = normal time + allowance	Standard time = normal time + allowance
3	Big data analysis	Limited amount of data analysis
4	The work of many employees is considered in the analysis	Performance rating equals the differences between employees
5	The use of local maximums and probabilities solves the reference number problem	Problem with specifying the reference quantity for operations repeated every certain number of cycles

5. AN EXAMPLE

Analysis of the production process using kernel density estimators requires interpretation of the data presented in graphical form (Table 2). The occurrence of a series of extremes indicates that a worker performs several activities at different frequencies. In the analysed examples (Table 2), in addition to the primary activity, the worker performs activities that are repeated in some work cycles. The right part of the graph indicates the occurrence of rare tasks, few disturbances or measurement errors. Unlike the method of time analysis using kernel estimators, the time study method makes it possible to determine the time standard for a work task on the basis of a few or a dozen time measurements. The use of the time study may result in the omission of some activities carried out by the worker. Analysis of the probability density plot indicates that the description of the process should include both the activities performed in each work cycle and those performed periodically. The analysis conducted with the use of kernel estimators identifies the cyclic nature of the conducted activities. Table 2 included both methods for determining the time standard, such as the time study and the proposed approach using kernel estimators, and a comparison is shown. The examples shown in Table 2 use mixed data, which is partly from the manufacturing process and partly from simulation.

Table 2. Results of the proposed approach

Case no	Probability for the global (maximum) extremum of the kernel density estimator p_{max}	Probability of local first extremum p_1	Probability of local second extremum p_2	Time value for the global extremum of the kernel density estimator $t_{p\ max}$	Work time of a rare tasks of type 1 (every certain number of cycles) t_{n1}	Work time of a rare tasks of type 2 (every certain number of cycles) t_{n2}	Normal time $t_{n\ estimator}$ determined by estimator	Normal time $t_{n\ time\ study}$ determined by time study	Kernel estimator $K(x)=\frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}}$ $\hat{f}(x\|h)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{x-x_i}{h}\right)$	Absolute error $\Delta t=\|t_{n\ estimator}-t_{n\ time\ study}\|$	Relative error $\delta=(\Delta t/t_{n\ time\ study})\cdot 100$
1	0.2400	0.0200		6.0000	16.0000		7.4936	7.3300		0.1636	2.2319
2	0.0850			133.0000			144.3050	134.5000		9.8050	7.2900
3	0.0900			383.0000			417.4700	384.2000		33.2700	8.6596
4	0.0800	0.0020	0.0020	380.0000	580.0000	600.0000	409.6045	394.2000		15.4045	3.9078
5	0.0700	0.0020	0.0020	30.0000	230.0000	235.0000	32.7821	35.2000		2.4179	6.8691
6	0.0700	0.0050		380.0000	600.0000		403.6530	392.3000		11.3530	2.8940

6. CONCLUSIONS

The application of artificial intelligence creates new opportunities for work measurement. Collecting big data from the production process is possible using deep neural networks [4]. Analysing data related to the production process requires development of a new approach to setting time standards. In the proposed approach, kernel estimators have been used, and formulas for setting time standards have been proposed. The comparison between the time study and the proposed approach has been presented. Based on six examples, the results of the proposed approach have been analysed. The relative error ranges from 2% to 9%. Technological operations with a duration from 7 to 417, including global and local extrema in the quantities of 0, 1, or 2, were analysed. The proposed approach does not use performance rating, which is necessary for establishing time standards, and depends on the experience. Therefore, the proposed approach is independent of employee's experience and is more objective.

The proposed method requires the development of a method useful for setting the parameter h (smoothing factor). In the presented approach, h was estimated. Future research focuses on finding a method for setting the h parameter in the kernel estimator useful in the proposed approach. The proposed approach is promising for automated time standard setting based on big data.

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