Assessment of the State of Production System Components for Digital Twins Technology

T. I. Buldakova and S. I. Suyatinov

Abstract The problem of assessment of the state of production systems is considered. The chapter is suggested applying the technology of digital twins to solve the problem of diagnosing and predicting the state of the components of the production system. The hierarchical structure of modern production is described, as well as the interaction of the production system and its digital twin. The correspondence of the system components and models of their state assessment is indicated. Methods and tools for assessing the state of the components of different hierarchical levels of the production system representation are proposed. As an example, the assessment of the state of stamp-tool production is considered and the models for assessing the state of its components for the digital twin are given. Also, a criterion and method for assessing the state of the upper organizational and technical level of this system are proposed.

Keywords Cyber-physical system · Production element · State assessment · Model · Digital twin

1 Introduction

An assessment of the state of the production system for the purpose of diagnosing it is an important and crucial task. In the process of its solution, they reveal, analyze and evaluate the level of efficiency and development of its various components (equipment, technology, personnel, resources, etc.). The problem is that production is a hierarchical structure, each level of which has its own specifics. At the same time, components of each level contribute to ensuring trouble-free and uninterrupted operation of the entire production. For the diagnosis of different types of components

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apply their methods and approaches. The methods of technical diagnostics applied to the lower hierarchical level have the most development [1–3].

There are three main types of technical diagnostics: (1) planned diagnostics—periodic testing of equipment performance according to a predetermined schedule; (2) unscheduled, emergency diagnostics—identifying the causes and conditions that caused the faults, and making informed decisions to eliminate them; (3) monitoring—recognition of the current technical condition of the equipment to predict possible failures. Regardless of what type of diagnosis is implemented, methods and means of its implementation are necessary. Moreover, at present, they are one of the most important factors for increasing the efficiency of using equipment, mechanisms, and machines in the industry [4–6].

At the same time, the problem of assessing the state of upper levels of the production system, in the process of their continuous monitoring, remains relevant.

2 Purpose of Research

The tasks of monitoring and assessing the state of production are particularly relevant for cyber-physical systems. Being fundamentally distributed, such systems are characterized by a high saturation of sensors and actuators, providing automatic operation of production facilities, minimizing maintenance personnel and visual control of equipment operation, especially at lower hierarchical levels of the production process [7–10].

At the same time, despite the high level of automation of information processing and management decision-making, an important element in cyber-physical systems remains a person who makes important decisions at various hierarchical levels of production [11–13]. At the dispatch level, the state of a human operator largely determines the quality indicators of the production process. The staff of the upper organizational and technical level ensures uninterrupted logistical support. For assessing the state of the entire enterprise, it is necessary to monitor the functional state of the upper organizational and technical level.

Currently, the problems of monitoring and predicting the state of the components of the production system can be successfully solved within the concept of digital twins. The concept is based on the technology of mathematical modeling of business processes of a production system and, in particular, the model of the dynamics of executive bodies, including the human operator. The concept of digital twins is a logical continuation of the development of CALS technologies, mathematical modeling and diagnostic models [14–16]. The technical realization of the digital twin became possible due to the development of computer technology, the Internet and wireless sensors.

This study aims to analyze the hierarchical levels of the production system, based on the requirements of assessing its state in the process of monitoring, as well as the development of criteria and methods for assessing the state of the upper organizational and technical level.

3 Representation Levels of the Production System

In the modern production system, it is possible to distinguish several hierarchical levels corresponding to various types of system components. The lower level includes production equipment (machine tools, mechanisms, machine equipment, and other production components), that process raw materials into the finished product following the technological route. At the middle level, we will include workers who support production processes, including the human operator, who manages complex equipment. The upper level of the production system is usually the level of management personnel who make the most responsible decisions on the material, technical and personnel support of production.

The structure of the system "real production—digital twin" is shown in Fig. 1. For simplicity, the division into levels is made on information types and not on the

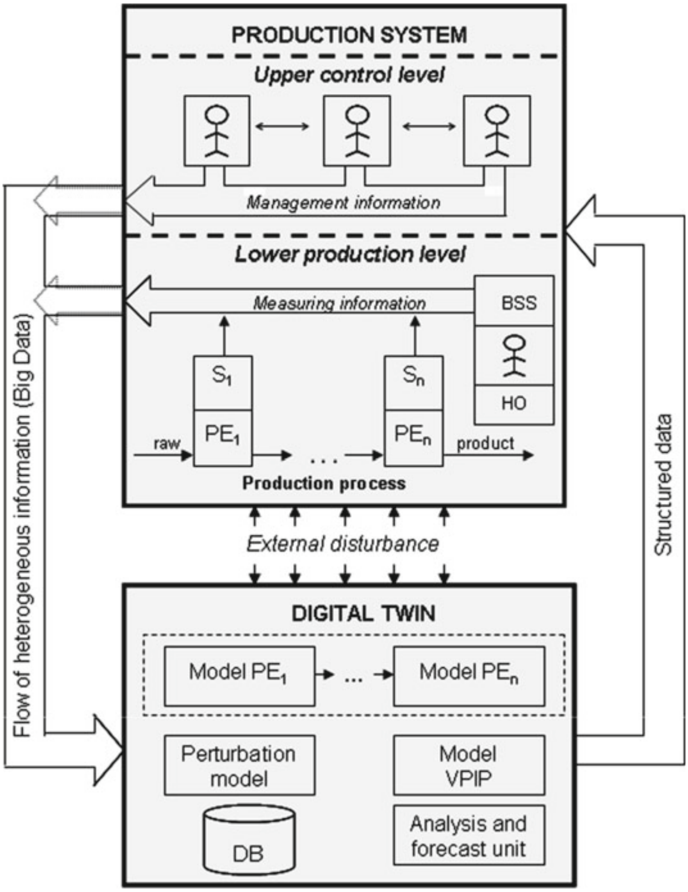

Fig. 1 Interaction of production system and digital twin

types of system components. Therefore, production is represented by a two-level hierarchical system, where the human operator is included in the lower production level.

The upper level of the production system is the organizational and technical level, the level of managerial personnel. Information on this level in the form of planning tasks, specifications, technological maps, standards, and other similar documentation is transmitted to the database (DB) of the digital twin. The lower level represents the sequence of production element (PE), processing raw materials into the finished product in accordance with the technological route. In this case, a human operator (HO) is included in the control loop at the lower level.

The state of production elements is estimated on the basis of signals recorded by various sensors $S_1, \ldots, S_{1n}$. To assess the state of a human operator, biosignal sensors (BSS) of various physiological nature are used. Measuring information recorded by sensors is transmitted via communication channels to a computer center, where a digital twin is implemented in the form of assessed by a virtual physiological image of a person (VPIP) [17–19].

From the point of view of technical implementation, the digital twin is a structured set of data and algorithms that allow one to programmatically simulate the state and behavior of the production system and its components under various external and internal influences. Therefore, using digital twin technology for diagnostics the production system, models are created for each hierarchical level, allowing the state assessment of the corresponding components.

On Fig. 2 there is the hierarchical structure of the representation of the production system components and models for assessing the state of its components for the digital twin technology.

Next, as a production system, we consider stamp-tool production (STP) (Fig. 3). We will highlight the main components responsible for the passage of the order for the manufacture of technical equipment and tools (TET).

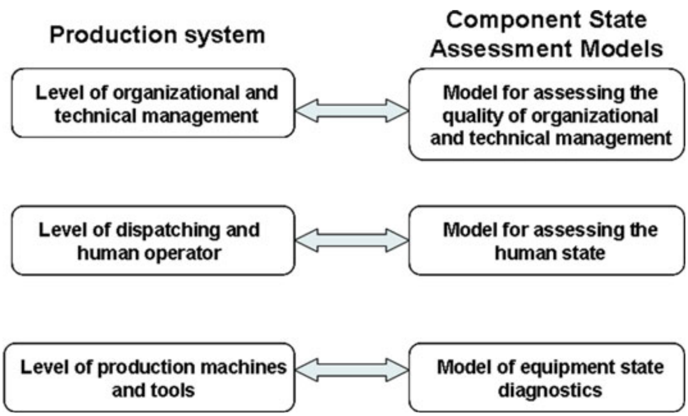

Fig. 2 Compliance of system components and its models

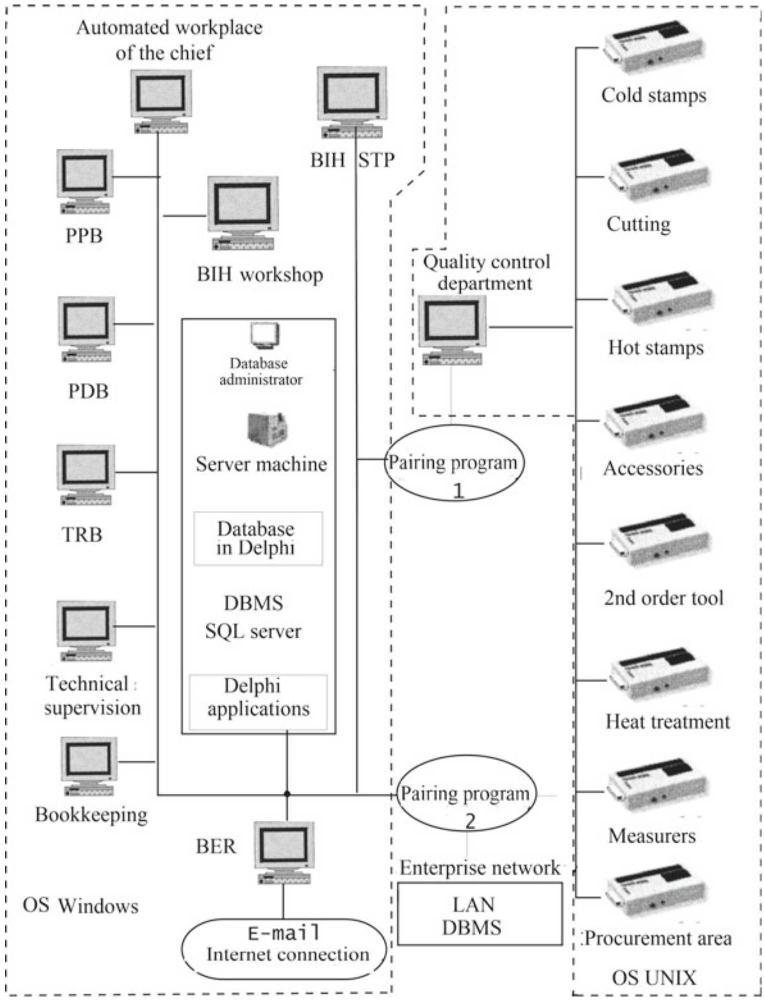

Fig. 3 The interaction of components STP

These include: planning and production bureau (PPB); planning and dispatch bureau (PDB); technology regulation bureau (TRB); bureau of technical supervision; bookkeeping; bureau of external relations (BER); bureau of instrumental house (BIH)—warehouses; quality control department and masters of production sites; technologists and designers engaged in coding cutting tools, stamps and their components.

Since it is impossible to operate personal computers under industrial production conditions, then modernized terminals BDT K 8901 (recorders) are used for operating data collection. The terminals, that control by a server on the Unix platform, are located directly in the workshop near the machines and production equipment.

Data from registrars arrive at the Unix server and are written to the intermediate database, from where they are read programmatically into a common database. Thus, the automated management system of the supply and production of TET allows in real time to collect and process the necessary information, and also to control the presence of the tool in all departments of the enterprise, as well as the passage of orders for its purchase and/or production.

4 Approaches for Assessing the State of Components of the Production System

At present, effective methods and means of assessing the working capacity of the production system under consideration at the lower (third) hierarchical level have been developed. Assessment of the state and diagnostics of operability can be performed in various ways, for example, using information-control and test benches based on SCADA technologies [20, 21]. An example of a diagnostic bench complex based on LabView is shown (Fig. 4). The complex can be used for diagnostics of machine tool elements.

This stand was used to diagnose the spindle feed-in grinding machines of the AGL series. The algorithm is worked out using LabVIEW software and a NI cRIO-9014 microcontroller with a real-time OS developed by National Instruments.

Assessment of the state and diagnosis of the system at the second level is primarily carried out to determine the performance of the person making decisions on the control of complex equipment and machinery. In such a high-tech environment, human interaction with information technology systems is becoming more complex and diverse, which creates a significant load on the operator and can lead to erroneous

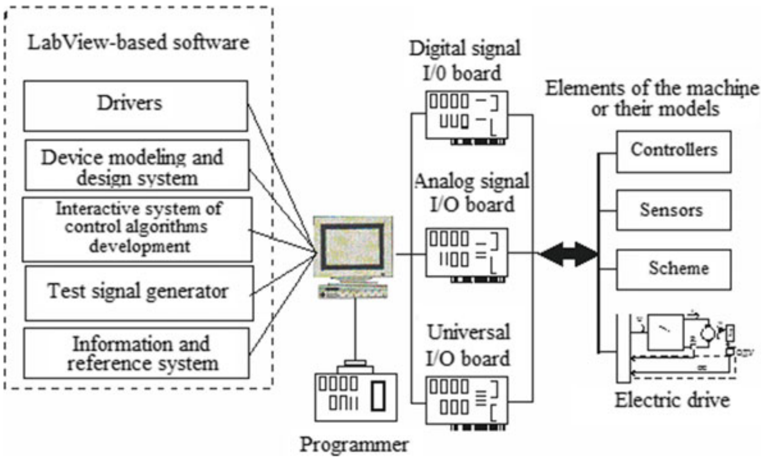

Fig. 4 Diagnostic bench complex

reactions in the control loop. Moreover, the activity of a human operator operating a complex device or equipment is characterized by high psycho-emotional stress, which can also have a negative impact on its performance. Therefore, in cyber-physical systems, it is necessary to constantly monitor the state of not only the technical means and equipment but also the human state.

Issues related to the assessment of the state of a human operator were studied in detail by the authors, for example, in [18, 19, 22, 23].

The first, upper level, associated with organizational and technical management, has a significant impact on the functioning of the entire production system. At this level, the most responsible decisions are made to ensure a clear and uninterrupted operation of the system. Therefore, criteria and methods are needed to assess the state of this level of management.

The production structure includes units of different types that are directly or indirectly related to each other. These various divisions and their relationships determine the complexity of the system. Various methods for estimating the complexity of production are known [24, 25]. Among them, the most generalized complexity estimate is entropy.

Existing approaches to the entropy estimation of production complexity are mainly used to assess the complexity of the equipment used. This assessment makes it possible to simplify production chains and reduce costs accordingly.

In [26], the entropy indicator is used to assess problems with the execution of orders caused by changes in customer requirements and the corresponding increase in the complexity of production. At the same time, the complexity of order execution is determined by the deviation of the planned deliveries from the deliveries modified by the customer. Note that the entropy complexity indicator can also be interpreted as an indicator of system organization, which can be used to assess its state. Therefore, it is proposed to accept the deviation from the planned indicators as initial information for assessing the state of the production system.

Then, to assess the functional state of the upper organizational and technical level of the cyber-physical system, an entropy indicator can be used, which is calculated based on the possible states of the production system. If the production operates in accordance with the planned tasks, then this state of the system corresponds to a certain indicator of organization. Various production disruptions lead to changes in interconnections and intensification of material and information flows. As a result, the entropy indicator of complexity increases, which indicates the occurrence of problems in the organization of production.

Consider the example of the production of cutting tools. Suppose that according to the plan it is necessary to manufacture n_j cutters in a day, where j denotes the number of the day of the planning period, and in fact, m_j cutters are made in a day. Then the daily deviations from the norm will be $d_j = n_j - m_j$. In this case, the value of d_j is an indicator of the state of the organizational and technical system in the manufacture of cutting tools. Then N deviation ranges of d_j are set and a histogram showing the probability of falling into each range is plotted. The entropy indicator is calculated by the known formula:

$$H(D) = -\sum_{i=1}^{N} p(d_i) \log_2 p(d_i). \tag{1}$$

Here H(D) is an indicator of the organization of the system in the production of cutting tools; $p(d_i)$ is the probability of hitting the deviations in the range i.

For a comprehensive assessment of the state of the organizational and technical system, it is necessary to take into account all material and information flows [27]. Then we get

$$H_\Sigma = -\sum_{i=1}^{M} \sum_{j=1}^{N_i} p_{ij} \log_2 p_{ij}. \tag{2}$$

Here H_Σ is an indicator of system organization; p_{ij} is probability that the resource i, (i = 1, ..., M), is in the state j, (j = 1, ..., N_i); M is number of resources (flows); N_i is the number of possible states for the resource i.

The advantage of the proposed criterion and method for assessing the state of the upper organizational and technical level is the availability of initial information, the ability to identify the most responsible and/or problematic production areas in the monitoring process.

5 Conclusion

Thus, a characteristic feature of cyber-physical systems is information monitoring and assessment of the state of production components of all hierarchical levels. The use of digital twin technology allows you to more effectively assess the state of the production system components.

Methods of diagnostics of the machine park, based on mathematical models of physical processes implemented in digital twins, have received the most development. Although methods of assessing the state of a human operator have a long history, they are still at the research stage. Methods and criteria for assessing the state of the organizational and technical system are at the stage of the problem statement and the choice of mathematical support. The proposed method of state estimation based on the entropy criterion is very promising, given its advantages.

Further research should be directed to the study of alternative options for assessing the state of the production system components. The final stage should be the development of a methodology for integrated assessment of the state of production systems.

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