Business Process Optimization in the Digitalization Era of Production

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ABSTRACT
Various business process optimization methods associated with industrial companies are reviewed, e.g. the processes of production planning, equipment and inventory maintenance as well as quality control. Case studies of Russian and foreign companies are provided. The author can conclude that digital technologies provide a significant advantage when implemented in an industrial production environment to the demands of Industry 4.0 technologies.

KEYWORDS:
Business process optimization, Industry 4.0, digital transformation, industry, quality control.

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1. INTRODUCTION
Much attention was paid to improving the production process in different periods of industrial development. The works of Ford, Crowther (1922), W. Deming (1943), F. Taylor, (1911), G. Gaunt (1903) and others laid the theoretical basis of modern methods for improving the efficiency of industrial enterprises. In many companies of the manufacturing sector, “six sigma”, the Total Quality Management system (TQM), and “Just-in-Time” (JIT) are widely used. Today, there is an active interest of the scientific community in the Industry 4.0 phenomenon (Lisowski, 2018; Tarasov, Popov, 2018; Roblek, Meško, Krapež, 2016). Technologies of the fourth industrial revolution (Industry 4.0) make it possible to carry out optimization measures of production processes at a qualitatively new level using digital technologies.

Consulting company PwC identifies eight core technologies of Industry 4.0: blockchain, unmanned devices, three-dimensional printing, virtual reality, augmented reality, Internet of things, artificial intelligence, robotics (Pooh, 2017). They have great potential in improving production processes with integrated and system use. Today, large domestic and foreign companies are actively exploring the possibility of introducing digital technologies to optimize key business processes. Significant results were achieved by PJSC NLMK, PJSC Sibur, Siemens AG, Intel and other industry leaders (Lisowski, 2018). The introduction of digital technology will reduce the cost of individual items up to 30% (Rojko, 2017).

The purpose of this work is to study approaches to optimize production processes using digital technologies. The central object of the study is introduction of digital technologies into the most significant and common production business processes: production planning, equipment maintenance and quality control.

2. PRODUCTION PLANNING
Organization of the production planning process often affects the overall efficiency of the production process, since at this stage of production the load on the equipment is distributed. Irrational capacity utilization can lead to downtime and lower output. An effective planning process involves:
• demand prediction;
• identifying production capacity to meet the demand;
• selection of alternatives that provide the highest level of efficiency;
• monitoring the implementation of plans;
• production plan adjustment (SMEtoolkit, [s.a.]).

Prediction is usually done using quantitative methods. The most common methods for calculating the potential demand for the products of an industrial company that carries out both standard and non-standard orders are coefficient method, linear regression and neural network (Table 1). The choice of prediction method is due to the presence of a streamlined data collection system and the company's ability to analyze the data. Compared to the neural network, linear regression (a quantitative method for product demand prediction (Dean, Xue, Tu, 2009)

Table 1

| Indicator | Coefficients | Linear regression | Neural network |
|-----------|--------------|------------------|---------------|
| Description | Coefficients between the resulting indicator and potential factors | Linear relationships between the resulting indicator and significant factors | Relationships of any nature between demand factors and the resulting indicator |
| Easy to count | + | + | — |
| Suitability for summary counting | + | + | — |
| Detailed result | — | — | + |
| Exact result | — | — | + |
| Intuitive conclusions | — | — | + |

Advantages

Inaccurate results in detailization | + | + | + |

The need for more data | — | + | — |

Lack of accounting for indirect links | — | + | — |

Difficult calculation | — | — | + |
Reliability Centered Maintenance and Business Centered basic concepts are highlighted: Total Productive Maintenance, measure of equipment repair after it is out of order. Prevent cases of malfunction. Corrective maintenance is a (Ding, Kamaruddin, 2015). Preventive maintenance involves the negative effects of equipment wear, many companies maintenance, increasing the risk of lower quality. To minimize corrective measures, the methodology of this concept allows you to answer three questions:

1. How do equipment failures occur?
2. What are the consequences of these failures for the company?
3. What effect can be achieved through preventive measures?

The concept can be implemented through the following steps:

- collection of information;
- description of functional block diagrams;
- evaluation of the most vulnerable functional areas;
- defect simulation;
- evaluation of the most critical defects;
- approbation of results using a decision tree;
- tasks gradation by importance;
- elaboration of preventive procedures;
- analysis of the effectiveness of the implemented approaches;
- system analysis and adjustment (Shin, Regikumar, 2016).

Industry 4.0 contains a wide range of technologies that allow companies to use the opportunities of digitalization in the field of maintenance and repair. Thus, at the Novolipetsk Metallurgical Combine, replacement of tuyeres of Rossiyanka blast furnace is carried out in accordance with the burning model of this piece of equipment built using machine learning. The model was based on studying current practices, collecting an array of historical data obtained with the use of sensors and laboratory tests. Prediction of equipment failure and timely appropriate adjustment measures, a quality control system for production processes can be arranged. In accordance with the practice of Renishaw consulting company, this system can be represented as a four-level pyramid: quality control is divided into informational (finished products), active (production process), preventive (equipment and materials) and preventive (external factors) (O'Regan, Prickett, Sethi et al., 2017. (Fig. 1).

Preventive control. The basis of control is provided by the monitoring system of the monitored parameter and the automated adjustment of its value to the required value in real time. With the help of digital sensors and the Internet of Things, you can fine-tune the process and optimal adjustment. For example, in industrial premises, great attention is paid to the environment, primarily humidity and air temperature.

To reduce the share of defective products in production, an analytical system for monitoring defects can be organized. Temperature control is provided by a switch system, proportional and integral systems (Temperature controller basics, [3.2]). For a switch system, an optimal temperature value, which must be maintained indefinitely, is set. In case of deviation from this value, the system automatically begins to heat / cool the air until the optimum point is reached. When introducing a switch system, as a rule, the temperature range is set so that the heating system does not start up with minimal deviations. Such solutions are the simplest and relatively cheap.

Proportional temperature control systems operate on a more complex algorithm: the optimal points can be built depending on time. This is relevant in production, where different conditions need to be maintained at different stages. Integrated systems not only take into account the environmental conditions, but are also able to change the optimal temperature points depending on the volume of production. This allows you to quickly respond to dramatic changes in the specificity of the production process.

Predictive control. As part of the transition to Industry 4.0, the development of measures to minimize the level of defects in production is of particular importance. Among the factors that may cause product defects, scientific work referred to the serviceability of equipment, the quality of input materials, duration of the work shift (as a factor in workers' fatigue) and environmental conditions, but are also able to change the optimal temperature points depending on the volume of production. This allows you to quickly respond to dramatic changes in the specificity of the production process.

Table 2: An example of a control registry of defects (Chongwatpol, 2015)

| Name     | Experience, months | Shift | Time | Model | Date of M&R | Type | Defect presence |
|----------|--------------------|-------|------|-------|-------------|------|----------------|
| Ivanov I.I. | 36                 | First | 11.30 | Z500  | 11.11.2018  | Glue | ProPan         |
| Petrov P.P. | 12                 | Second| 2140 | Z500  | 11.07.2018  | Glue | ProPan         |
| Sidorov S.S. | 2                  | Second| 23.20| Z500  | 25.03.2018  | Glue | ProPan         |
| Kurbatov K.K. | 57                | First | 17.20| Z500  | 01.09.2018  | Glue | ProPan         |

Fig. 1. Four levels of quality management in production (O'Regan, Prickett, Sethi et al., 2017)
Digital technologies will facilitate the work of expert commissions to eliminate defects in enterprises. Expert meetings can be held remotely via electronic communications. An expert live inspection in stages of production processes requires the company in his area of responsibility. For each unit, a time limit on the formation of recommendations should be set. After receiving recommendations from all members of the commission, the production manager of the product takes the appropriate measures to eliminate the defects and form a report. This report can be attached to general information on working with a specific claim.

5. CONCLUSION

In the transition to the Paradigm of Industry 4.0, previously developed methods for optimizing production business processes remain relevant. The use of digitalization technologies will allow the use of such optimization methods that were previously unavailable due to the lack of the necessary infrastructure. The company is responsible for choosing specific methods and technologies used, since it may have its own strategic priorities and resource constraints. Only an optimal combination of implemented measures and their compliance with existing and future needs will allow companies to make cost-effective and efficient business optimization.

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