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Labor Demand Forecast in the Context of Robotics Implementation in Russian Agriculture

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Abstract

In the context of the implementation of robotics in agriculture, there is a decrease in the need for workers engaged in low-skilled labor and an increase in the need for specialists interacting with robots. The number of tractor drivers decreased by 12%, machine milking operators by 11.2%, pig-farm workers by 41.6%, while the demand for robotic milking operators increased by 30% and robotic maintenance technicians doubled. The study aims to develop an optimization model for forecasting the need for labor resources in the context of the use of robotics in agriculture. The standard need for workers at the current rates of robotization of agriculture was used as a limitation of the model. Under the basic scenario of robotization of the industry, a decrease in the need for milking machine operators will be 57 people, cattle-farm workers 49 people, the need for robotic milking operators will increase 15 people until 2024, and for robotics maintenance technicians by 3 people. Under the optimistic scenario of robotization of agriculture, the need for robotic milking operators will increase by 58 people until 2024, and in robotics maintenance technicians by 12 people. The executive authorities, managers and specialists of agricultural organizations can use this model to forecast labor needs to determine the surplus or deficit of certain workers.

Disciplinary: Agricultural Management, Labor Studies.

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1 Introduction

Forecasting the need for labor resources is a significant strategic and management practice for government and commercial organizations [1,2]. In addition, a well-developed forecasting plan, for the number of personnel, can be used to meet the changing needs in dynamic labor markets such as agriculture. Accurate forecasting of requirements in labor force is a difficult task for any industry, especially for as rapidly changing as agriculture, as the output often fluctuates greatly.

Some scientists have developed models for forecasting the need in the labor force, which meets the need for personnel [3,4]. The use of multiple regression and econometric methods in these forecasting models for labor demand depends on several key variables such as employment and wages. These models are quite complex and involve several processes for assessing key variables that can change dramatically and thus affect the accuracy of the forecast. An alternative to the above-mentioned approaches is a labor multiplier method, which allows determining the relationship between a volume of agricultural production and the need for labor forces.

2 Materials and Methods.

Currently, the Russian Federation has adopted and developed the concept of scientific and technological development of digital agriculture "Digital Agriculture". According to this program, there is a roadmap for monitoring its implementation. One of the objectives of this program is the development of a digital environment for distance agricultural education and the market of professional agricultural consulting [5]. Other tasks are to increase the attractiveness of work in agriculture, increase the demand for IT specialists in the agricultural sector, and increase the level of income in rural areas [6].

Assistance is needed in the development and implementation of new educational programs [7] and training standards on innovative digital farming technologies in the system of higher and secondary vocational education (including the use of direct seeding, precision farming technologies, biotechnologies, etc.), advanced training courses for personnel in the agro-industrial complex, providing a set of measures for the transfer of knowledge and conservation agriculture technologies and biotechnology in agricultural production [8, 9].

In accordance with these tasks, by 2024, the specialized universities should give first graduates and fully implement programs for training specialists in data processing, platform support, microelectronics and digital equipment for the needs of agriculture. Thus, the activities of executive authorities and specialized educational institutions should involve the task of determining the need for training personnel capable of mastering robotics and other digital technologies. The solution to these problems is associated with the development of an appropriate optimization model.

For this purpose, the economic growth model of R. Solow is taken [10]; according to this model technological progress increases labor productivity:

$$Y_j\,(t) = F\,(F_j(t), A_j(t), L_j(t)) \qquad (1),$$

where the variable *Yj (t)* is the output of the final product in *j*-country, and the variables *Fj(t), Lj(t)* are the capital stock and labor supply, respectively. The variable *Aj(t)* describes the technology in a given economy, which differs between countries and changes over time.

The study aims to develop an optimization model for forecasting the demand for labor resources in the context of the use of robotics in agriculture.

3 Results and Discussion

Recent times are characterized by the advent of several technologies, which, on the one hand, reduce the need for labor resources, and on the other hand, cause the need to improve the qualifications of workers interacting with these technologies. It is known from our empirical observations that these results are mainly presented in agricultural organizations by digital technologies, primarily, by robotics, including those used in milking. For convenience, we will assume that digital workplaces are serviced by skilled workers, while unskilled workers deal with traditional technology workplaces.

The main conclusions from empirical studies are that, despite the assumption that digital technologies (in particular, robotics) are available for implementation, there are significant differences in technologies between agricultural organizations operating in similar conditions. This may be due to the provision of organizations with qualified employees who directly service the new equipment, and with the availability of managers who do not have sufficient organizational and management skills for their implementation (Figure 1).

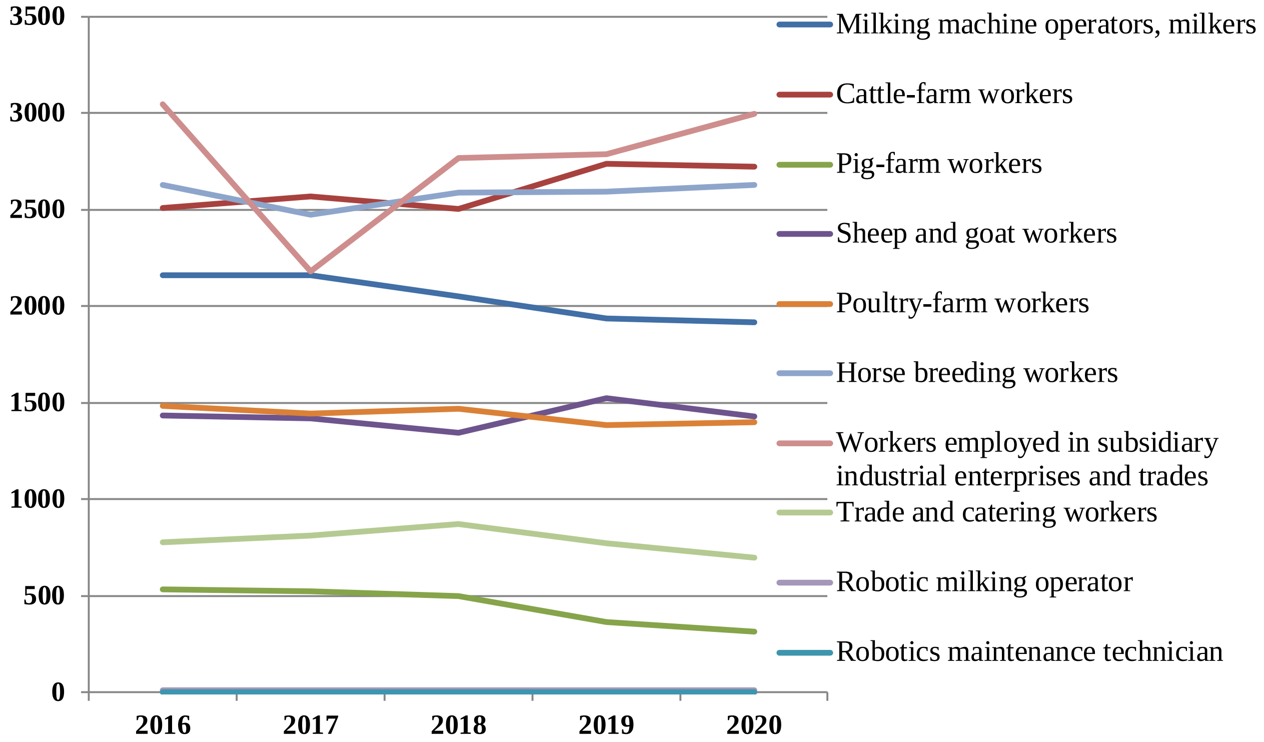

Figure 1: Availability of labor resources in agricultural organizations, people

Figure 1 shows the total number of agricultural workers in the region decreased from 28,670 to 26,201 people, or by 8.9%. At the same time, the smallest decrease is observed in the category of workers 0.9% and managers 5.9%. The greatest decrease is in professions engaged mainly in manual labor. Thus, the number of tractor drivers decreased to 2,878 people or by 12%, machine milking operators to 1,917 people or by 11.2%, pig-farm workers to 313 people or by 41.6%. There is a relatively stable number of workers employed in poultry farming and workers employed in subsidiary industrial enterprises and trades. It should be noted that the number of robotic milking operators grew by 30% over the studied period, and the number of robotic maintenance technicians doubled. However, the number of workers in these categories remains relatively low.

The development of an optimization model for the formation of agricultural labor resources in the context of digital transformation is a rather difficult task. This is associated with certain difficulties, which include:

First, digital transformation in agricultural organizations is connected with the development of rural infrastructure. Thus, there is an increase in the spread of the Internet in rural areas. According to the Public Opinion Foundation, the dynamics of Internet spread increased from 10% in 2003 to 72% in 2018 [29] in federal districts and settlements of various types. However, in some cases, there is a significant lag in the development of rural infrastructure from the national average. The low level or lack of appropriate infrastructure can decrease the use of digital technologies, in particular robotics. This can result in a demand for workers interacting only with traditional technologies.

Second, it is difficult to explain why some organizations are implementing digital technologies and robotics that can significantly increase labor productivity, while others are not. Some studies indicate that the key factor influencing the decision to introduce new technologies is likely to be the qualifications of workers. This is approximated with the proportion of workers not employed in the manufacturing sector.

According to the International Labor Organization (ILO), a share of agricultural workers in the total labor force had fallen from 81.0% to 48.2% in developing countries and from 35.0% to 4.2% in developed countries by 2014. The shortage of people working on farms is becoming a persistent problem everywhere. In the Asia-Pacific region, especially Japan, the number of people working on farms fell from 2.2 million in 2004 to 1.7 million in 2014. A significant decrease in the labor force of about 12.8% is also observed in the European agricultural sector. This decrease in the labor force is observed because young people do not become farmers, they find it unattractive, and the lack of qualified personnel encourages the introduction of agricultural automation technologies. Milking robots are one of the most successful and important innovations in the dairy farming system. According to the International Federation of Robotics, milking robots are up to 85% of the total number of robots used in the industry. The average sales of milking robots grew by about 9.4% in 2016-2017. Almost 20,000 dairy farms have installed robots in Western Europe, Canada, the USA, China and Japan. Factors such as increased milking frequency and high labor flexibility are driving the robotic milking robot market.

Figure 2 shows the number of robots used in agriculture in the Sverdlovsk region, as of 1 January 2020 in accordance with the data in and the data of the Ministry of Agro-industrial complex and the consumer market of the Sverdlovsk Region, 45 milking robots and three feed pushers have been installed and are used.

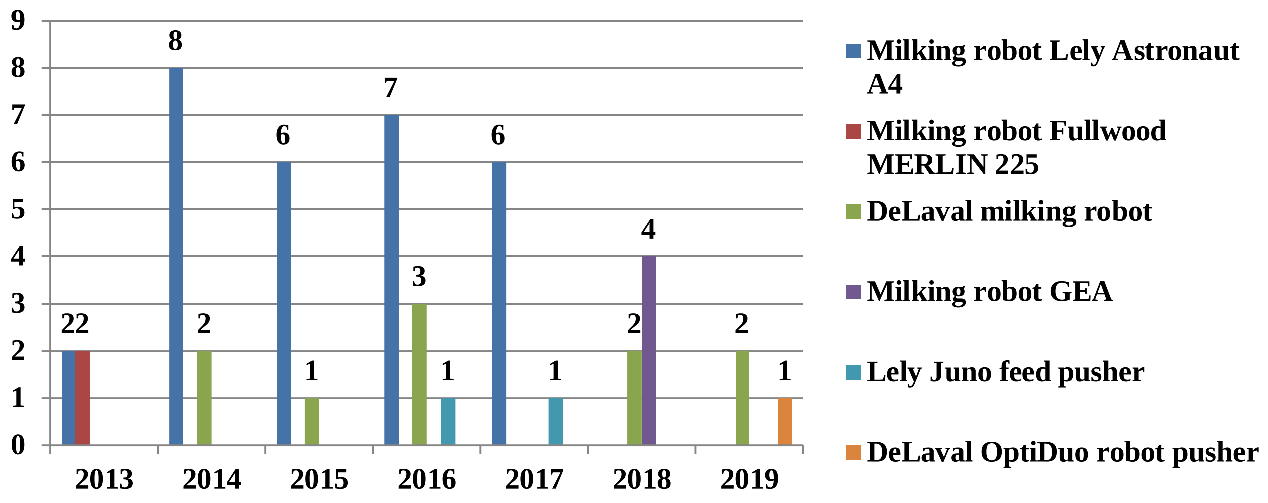

Figure 2: Dynamics of the implementation of robotics in agriculture in the Sverdlovsk region, pcs.

To develop a model of the need for agricultural labor resources in the context of the implementation of robotics, we assume that all agricultural organizations are represented by two groups. The first group includes organizations that implement digital technologies and, in particular, robotics. For simplicity, assume that these organizations have a large number of such jobs, but there are jobs without digital technologies and robotics. The second group consists of agricultural organizations that do not introduce digital technologies and robotics into production; they can be put as traditional organizations. For simplicity, assume that workers in these organizations are predominantly employed in unskilled labor, and the number of jobs with digital technologies and robotics is relatively small. At the same time, the qualifications of employees of organizations with digital technologies are better than the qualifications of employees of organizations where these technologies are not implemented. So, we have

$$\frac{Kr}{Fr} > \frac{Ko}{Fo} \qquad (2),$$

where K_r is the number of skilled workers in organizations with digital technologies and robotics;

F_r is the number of unskilled workers in organizations with digital technologies and robotics;

K_o is the number of skilled workers in traditional organizations;

F_o is the number of unskilled workers in traditional organizations.

Let us also assume that all agricultural organizations have equal access to a set of technologies (access to suppliers), have appropriate infrastructure for their implementation. At the same time, we find that all the differences in labor productivity are a result of possible discrepancies between technologies and the qualifications of workers.

Assume that the Y-production function of s-agricultural output at the t-time period is:

$$\mathrm{Y(s, t)} = \left(\int_0^{N_L(t)} X_L\,(s,v,t)\,dv\right)((1-\mathrm{i})\,\mathrm{l_j}\,(\mathrm{s, t})) + \left(\int_0^{N_H(t)} X_H\,(s,u,t)dv\right)(\mathrm{i, h_j}\,(\mathrm{s, t})) \qquad (3),$$

where l_j *(s, t)* is the number of unskilled workers employed in the production of s-agricultural products at the t-time period;

h_j *(s, t)* - the number of skilled workers employed in the production of *s*-agricultural products at the *t*-time period;

(1– *i*) - labor productivity of unskilled workers;

i - labor productivity of skilled workers;

X_L *(s, v, t)* - the number of machines of *v*-type that are used by unskilled workers;

X_H *(s, u, t)* - the number of *u*-type machines used by skilled workers;

N_L *(t)* - the number of types of machines used by unskilled workers;

N_H *(t)* - the number of types of machines used by skilled workers.

Thus, both skilled workers, applying the achievements of scientific and technological progress, and unskilled workers are employed in the production of agricultural products. Here, the variable *lj (s, t)* is the number of unskilled workers, and the variable *hj (s, t)* is the number of skilled workers employed in *s*-agricultural production at the *t*-time period. At the same time, the labor productivity of unskilled workers *(1– i)* is lower than that of *i*-skilled workers. Finally, the variable X_H *(s, u, t)* is the number of *u*-type machines used by skilled workers, and the variable X_L *(s, v, t)* is the number of *v*-type machines used by the rest of the workers. And the number of types of machines used by skilled and unskilled workers differs and is N_L *(t) and* N_H *(t)*, respectively.

Based on the model above, we consider it necessary to propose a methodology for assessing the need for agriculture in labor resources (T_R) in the context of digital transformation,

$$T_R = \int_0^{P_L(t)} lj(s,t)dv \times X_L\,(s, w, v, t) + \int_0^{P_H(t)} hj(s,t)\,dv \times X_H\,(s, w\,u, t) \qquad (4),$$

where l_j *(s, t)* is the number of unskilled workers employed in the production of *s*-agricultural products at the *t*-time period;

h_j *(s, t)* - the number of skilled workers employed in the production of *s*-agricultural products at the *t*-time period;

X_L *(s, v, t)* - the number of *v*-type machines that are used by unskilled workers;

X_H *(s, u, t)* - the number of *u*-type machines used by skilled workers;

P_L *(t)* - the number of professions of unskilled workers employed in the production of *s*-agricultural products at the *t*-time period;

P_H *(t)* - the number of professions of skilled workers employed in the production of *s*-agricultural products at the *t*-time period;

W - a coefficient characterizing an increase or decrease in the demand for labor resources in various professions.

This model already has known parameters. In particular, the variable l_j *(s, t)* is the number of unskilled workers, and the variable h_j *(s, t)* is the number of skilled workers employed in *s*-agricultural production at the *t*-time period. The variables X_L *(s, v, t)* and X_H *(s, u, t)* are the number of machines used by unskilled and skilled workers, respectively. At the same time, the *v*-type machines are traditional machines and equipment, and the *u*-type are machines and equipment used in the context of digital transformation. It is known from previous empirical results that it is mainly robotics used in milking and feed pushing. The number of professions for skilled and unskilled workers differs and is P_L (t) and P_H (t), respectively. The *w*-coefficient, characterizing an increase or decrease in the demand for labor resources in various professions, can be positive if there is an increase in the group of professions, and negative if there is a decrease in the need for these professions.

Using the presented methodology, it is possible to forecast the demand for labor resources in agriculture in the Sverdlovsk region in the context of further robotization. And the existing average annual rates of implementing robotics in agriculture of the region will be used. Thus, in addition by 2024, the number of robotics will have been 68 (Table 1).

Table 1: Forecasted number of workers at the planned rates of implementing farms with robotics, people

Employee category	Standard need	The need for workers until 2024 at the current pace of industry robotization	The need for workers until 2024 when increasing the livestock at robotic milking up to 5%
Milking machine operator	-1.30	-57	-222
Cattle-farm worker	-0.37	-49	-191
Robotics maintenance technician	0.07	3	12
Robotic milking operator	0.34	15	58
Total number of unskilled workers, people	-	-106	-413
Total number of skilled workers, people	-	18	70

Thus, while at the current pace of implementing digital technologies, significant changes will have occurred by 2024. So, at the current pace of robotization, the need for unskilled workers will significantly decrease. The calculations according to the proposed optimization model show that the decrease in the need for milking machine operators will be 57 people, cattle-farm workers 49 people. The total decrease in the number of unskilled workers will be 106 people until 2024. The need for labor resources that are capable to interact with digital technologies will increase. Thus, the need for robotic milking operators will increase by 15 people until 2024, for robotic maintenance technicians by 3 people. The total need for skilled workers will be 18 people at the current pace of industry robotization.

4 Conclusion

It is possible to assume a development scenario when the pace of robotization will exceed the current one. At the rate of robotization, which makes it possible to transfer 5% of the total cattle population to robotic milking by 2024, the decrease in the need for milking machine operators will be 222 people, and for cattle-farm workers - 191. The total decrease of unskilled workers will be 413 people until 2024 with the transfer of 5% of the livestock to robotic milking. The need for robotic milking operators will increase by 58 people until 2024, and for robotics maintenance technicians by 12 people. The total need for skilled workers will be 70 people at the rate of industry robotization, which makes it possible to transfer 5% of the cattle population to robotic milking. A further increase in the intensity of the use of digital technologies in agriculture can cause a significant transformation in the process of training labor resources. These changes include the emergence of new professions in areas of employment, the emergence of new types of employment, the transformation of demand and supply for labor forces at regional and local labor markets. The transformation in spheres of work can occur mainly from a specialist engaged in manual labor to a specialist engaged in mental labor.

5 Availability of Data and Material

Data can be made available by contacting the corresponding author.

6 Acknowledgements

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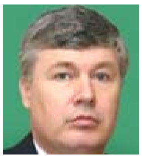

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