Diagnostic method and device for evaluating and forecasting the technical condition of farm machinery in operation

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Abstract

The paper discusses methods and ways to diagnose the technical condition of agricultural machines and harvesters, existing practices, and approaches to get reliable data on the current health of the machinery used. The device for assessing and predicting machines' technical condition includes software and technical means developed with virtual technologies to measure diagnostic parameters of the machinery. The main device elements are digital sensors with physical modifiers (pressure, temperature, medium composition and motion sensors, a-d converters with signal amplifiers), software to configure data gathering, and output to conduct analyses and produce recommendations. The core of the present approach is the technology of virtual prediction of breakdowns by changes in the technical condition parameters. It is based on modular devices, software with an interface that collects and processes data and provides a complete set of failure diagnostics and forecasting. The given method based on a device operating in the information and communication network increases farm machinery's performance. Furthermore, it reduces operating costs due to the prevention of expensive breakdowns, individual forecasting, and scheduled maintenance of machines in operation. The approach under consideration was applied in the laboratory of digital engineering technologies of the Bashkir State Agrarian University Republic of Bashkortostan of the Russian Federation. The given work is aimed to boost the efficiency of the farm machinery diagnostics and maintenance system by applying a virtual breakdown prediction technology to conduct an automated evaluation, registration, and analysis of a machine's condition. It can be achieved by developing software and technical means to register data and their structure systematization.

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Introduction

The Russian agricultural industry ensures the country's food security, which is one of the key national security strategies (Presidential Decree of the Russian Federation, 2020). Therefore, great attention is paid to the intensive development of agriculture, strengthening the rural economy, and increasing the rural population's income and living conditions due to the higher output of small and larger farming entities (Bulat *et al*., 2018; Zangiev *et al*., 2001). However, currently, there is not enough farm machinery and technologies in Russia (Fisinin *et al*., 2009). As a result, there is a need for highly efficient fault-free machines to apply available technologies in agricultural production. This situation is primarily since the possibilities of effective use of the technology are not limited to the third level of technical cooperation.

Most researchers consider tools and methods that are time-consuming and require a highly-qualified diagnostics technician. All these factors make them unfavorable for the continuous day-to-day control of the machinery's technical condition.

The extent of prior research

The development of electronic technologies and measurement and calculation equipment helped to model non-linear dynamic processes and create methods for the non-continuous reading of machinery indicators under operational conditions using computational platforms.

Azzoni *et al*. (1999), Ball *et al*. (2000), Bulat *et al*. (2017), Dorokhov (2010), Espadafor *et al*. (2014), Gabitov *et al*. (2019), Johnston and Shusto (1987), Johnson and Troy (2009), Malaczynski and Van der Poel (2010), Mamala *et al*. (2011), Schmidt *et al*. (2000), Subasinghe *et al*. (2015), Taglialatela *et al*. (2009), Taraza (1993), Williams (1996), Williams and Witter (2001) and others study issues of improving diagnostics methods by measurement and information systems. These authors describe initial conditions for theoretical research of an operating machine-tractor aggregate (MTA) as a dynamic system. It should be noted, that Russian diagnostic tools 'Avtoas-Ekspress', 'Skantronic 2', 'SMS Diagnostics', v.3.x USB, 'Imitator IDK-2', 'IMD-TsM', based on this principle, and foreign analogues 'CombiLoader 1S', 'Reiner-3000', 'PCMSCA N Dyno', 'Insoric 3G' are not widely used in service centres of agricultural enterprises (Bosch, n.d.; Rizzoni, 1989; Cavallo *et al*., 2015; Buklagin, 2016). Firstly, it is due to the lack of a virtual machine and a high-speed data connection. Secondly, it results from the operator's faulty connection and imperfect testing of the field conditions machinery. Thirdly, there are difficulties in transmitting large amounts of measurements while a machine is operating. Fourthly, there is uncertainty in the measurement of non-linear changes, as time and speed.

Fifthly, the need to test standard operating conditions requires avoiding the actual values of the intermediate indicators. Finally, testing tools are not perfect in terms of the methods and measurement result processing algorithms used.

Johnson identified the need for methods to diagnose transmission and the engine based on the torque changes. However, he claims that torque modeling is necessary only to develop dynamic tests (Johnson and Troy, 2009). Mamala *et al*. (2011) present a dynamic method to evaluate a moving vehicle's parameters in real operating conditions using data transmission CAN-BUS. The authors test a car's acceleration and velocity to estimate dynamic characteristics as acceleration power and losses. However, they do not study failure forecasting.

Dorokhov suggests determining the remaining lifetime of mechanism parts t_0 by equation (Dorokhov, 2010):

$$t_r = t_{av} \pm n \cdot \sigma_m - t_c \qquad (1)$$

where t_r stands for the remaining lifetime, operation hour;
t_{av} is the average service life, operation hour;
n - coefficient dependent on C, a confidence level of trouble-free operation, in machine-building industry n=1.96 if C=95%;
σ_m is the root-mean-square deviation of the probability of a malfunction in operation, operation hour;
t_c is the current life length, operation hour;
t_{av} value was determined based on the statistical data, while the n coefficient was found based on the generalized data for machine-building industry products. t_c was specified at the vehicle's arrival on maintenance service (MS).

The current technical development level makes it possible to eliminate restrictions in implementing the method of continuous failure diagnostics and predicting and developing mathematic tools for calculations (Raikwar *et al*., 2019). Computational technologies in integrating partial derivatives according to their theoretical regressional dependencies help analyze the function of measured parameters in transient modes. Then this process can be modeled for diagnostics and prediction purposes (Zhang *et al*., 2013; Mudarisov *et al*., 2017; Staszak *et al*., 2018). Studies of dynamic changes provided specific mathematical relations describing differential equation coefficients to solve identifying algorithms. These algorithms are in the heart of a tool to diagnose an engine under operating conditions.

The given research aimed to increase the operational efficiency of Russian-made car and tractor machinery by developing a method to assess the technical conditions and requirements for diagnostic tools according to operating parameters resulting from modeling and forecasting ongoing processes.

Materials and methods

The offered method is based on a mathematical algorithm (Insafuddinov *et al*., 2013), implemented in an electronic unit (Bashirov and Insafuddinov, 2012). It determines the minimum useful life of a machine and limits possible breakdowns. This aim was achieved by analysing a farm machinery's structural mathematical model M(I) as a controlled target (CT). Therefore, it can be presented as follows:

$$M(D)=(N,S,Y),$$

where N is the number of elements that make up the model;
D is the range of similarity;
$Y=f(\gamma, \zeta)$ stands for a set of conditions and rules that determine the dependences of γ on different types of ζ interaction.

The functional scheme of the CT can be described by a set of characteristics that define its parameters $\vec{P} = \{q_i\}, i=l,x$ and operators' basis $\vec{S} = \{S_i\} i=l,y$ that specify the relations between these indicators (Figure 1).

The CT parameters are constant and variable values change over time. They characterize a machine's condition and stipulate properties and characteristics for a specific period. These values are determined by the diagnostic device that scans S1, S2..., S_i subsystems, including M diagnostic units (Figure 2). Units that reduce the reliability of the CT on the whole need to be tested first. For this purpose, pressure (p), temperature (t), rotation frequency (ω), move frequency (δ) values determined by corresponding sensors are transmitted to the electronic unit of the continuous diagnostic system wired or wireless.

Every machinery can be equipped both with regular measuring devices that characterize its performance and auxiliary testers S_1, S_2.... S_i. Parameters describing the characteristics of a machine are considered input values. Output indicators will be available during operation.

All the CT parameters can be divided into four sets: $\vec{M} = \{\vec{W}, \vec{\alpha}, \vec{\beta}, \vec{\gamma}\}$ with $\vec{W}$ = 240 being variable coordinates; $\vec{\alpha} = \{\vec{\alpha_i}\}$ - internal parameters; $\vec{\gamma} = \{\vec{\gamma_i}\}$ *at* $i = l, r$ representing the CT output data.

The CT phase variables are the time functions τ_i. They evaluate the CT condition for the given period τ.

The phase variables include $\vec{W}$ include $\vec{X} = \{\vec{X_i}\}$ at $i = l, s$ external (input) phase variables, representing a set of input effects; $\vec{Y} = \{\vec{y_i}\}$ at $i = l, \tau$ are output phase variables that indicate a variety of the CT reactions; $\vec{Z} = \{\vec{z_i}\}$ at $i = l, h$ are internal phase variables that show different CT states. An operator equation interconnects the input and output phase variable vectors $\vec{Y} = \vec{P}\{\vec{X}\}$. Here *Pi* operator from $\vec{P}$ multitude presents a relation that assigns each element x_i from a set of input phase variables $\vec{X}$ exactly one or one-to-one element y_i from a set of output phase variables $\vec{Y}$.

The CT external parameters $\vec{\alpha} = \{\vec{\alpha_i}\}$ are the values that define properties of functional units that make the CT and sets $\vec{M} = \overrightarrow{M(\beta)}$ described by operators. The CT output parameters are physical quantities. Their numerical values characterize CT's operation quality. A set of output parameters $\vec{\gamma} = \{\vec{\gamma_i}\}$ provide a quantitive assessment of the CT's operation process quality: $\vec{\gamma} = R_1\{\vec{M}, \vec{\alpha}, \vec{\beta}\}$, where $\vec{M}$ is a basis of operators, representing the structure of the CT. In computer modeling of parameter assessment $\vec{\gamma} = R_2\{\vec{y_i}(\tau)\}$ at $0<\tau\leq\tau_o$, τ_o is the time to process the ongoing assessment.

The generalized mathematical model of the CT can be presented with an operation algorithm shown in Figure 2:

$\overrightarrow{Y(\tau)} = \overrightarrow{S(\beta)}\vec{X}(\vec{\alpha_i},\tau)$. $\vec{X} = \vec{X}(\vec{\alpha_i},\tau)$ *and* $\vec{\beta} = \{\vec{\beta_i}\}$ values can be specified by the time functions (Chernoivanov *et al*., 2017).

The CT's output parameters result from sample processing of an output variable $\vec{Y} = \{\vec{y_i}\}$ at $i = l, V$; S unit comprises s independent input phase variables, $\vec{X} = \vec{X}(\vec{\alpha_i},\tau)$, $0 < \tau < T_{h}$, entering the processing unit. The latter is presented digitally as a mathematical model of the CT that shows its parameters. Unit F_2 is responsible for $\vec{Y} = \{\vec{y_i}\}$ sample converting and statistical processing. As a result, the output parameters of the y* system are assessed. These evaluations are compared with nominal values of the output data $\vec{Y} = \{\vec{y_n}\}$. Further modeling depends on this comparison.

On theoretical grounds, the diagnostic process is as follows. First, there is a node parameter measured by a specific sensor with a reasonable error. Second, its value range is not known beforehand.

As possible conditions $V(D_i)$ can be derived from statistical data, the system entropy $S(D)$ can be described by equation 2:

$$S(D)=\sum_{i=1}^{n} V(D_i)\log_2 V(D_i) \qquad (2)$$

In practice, the CT's condition becomes available after complete expert testing by a set of signs K (estimated parameters). It equals D_1, then $P(D_1)=1$, $P(Di)=0$ $(i=2, \ldots, n)$. After conducting full expert testing, the system entropy is $S(D/K)=0$. The expert value of the test is $J_D(K)=Z_D(K)=H(D)- H(D/K)=H(D)$.

The diagnostics and prognostics principle of the method under consideration implies measuring output values for adjustable and technological parameters of D_i sensors to accepted (required) ranges being from minimal vales $x_{i\ min}$ to maximum ones $x_{i\ max}$.

$$x_i \rightarrow [x_{i\ min}, x_{i\ max}],\ i=1,2\ \ldots,\ n. \qquad (3)$$

Diagnostics uses signals of the operational profile of a machine, describing its performance. The completeness and reliability of the data transmitted to the system depend on the sensor quantity and type. The sensor quantity determines the complexity of a machine and affects the cost of the whole system. Sensor types specify data variety and features of the unit receiving signals. Sensor errors in domestic machines are permissible for drivers, but they can not be used in the method under consideration for being above limiting errors of machine parameters and operating conditions. For this reason, versatile sensors-markers that fit most of the units of different farm machinery were selected (Figure 3).

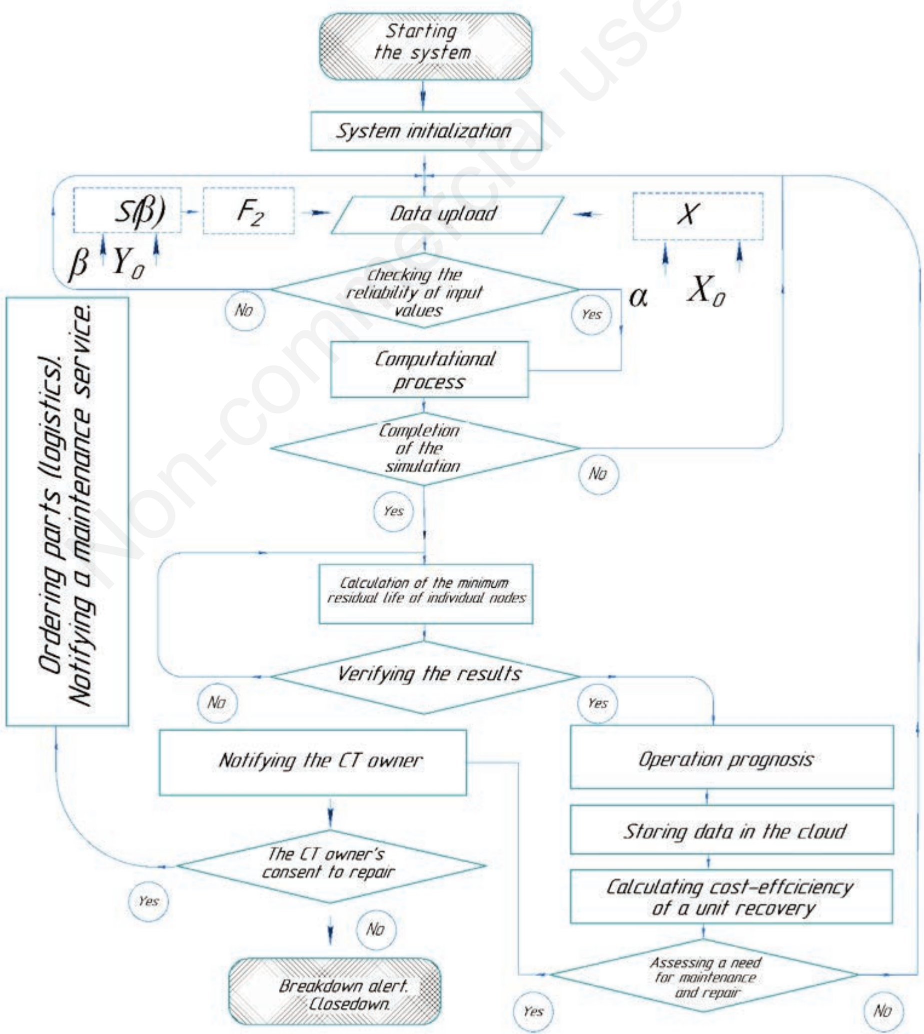

Figure 1. Operation algorithm of the modeled controlled target (CT) under the offered method.

Machine inspection was conducted in real operating conditions by modeling complicated operating processes based on the queueing theory, observation, and experiment methods. The tractor MTZ-82.1 'Belarus' is an experimental machine with a front-end loader 'Universal 800S', powered by 60 kW engine D-243S2. Field experiments were conducted in private farm Kalinina, located in the Diurtiuli district of the Bashkortostan Republic during 2020 (Figure 4).

The developed electronic unit 1) was mounted in the tractor cab and powered by a 12 V fuse box. The fuel consumption meter 'DFM-220-A-P' (2) was installed in the low-pressure region between a fuel-injection pump and a fine fuel filter connected with an overflow valve to an overflow line. A GSM transmitter was mounted at the top of the tractor cab. An oil quality sensor was installed instead of the crankcase drain plug.

The remaining useful life was prognosed by evaluating failure-free operation until the next maintenance. If the remaining useful life value is $\tau_o > \tau_i$, the current condition of the diagnosed mechanism will provide its fault-free performance until the scheduled maintenance. If the remaining useful life indicator τ_o is less than the arranged diagnostics interval τ_i, an engine should be withdrawn for repair.

Results and discussion

Standard values of technical condition parameters received as the result of the CT experimental studies are presented in Table 1. Pressure in the oil line, being of excess value, is highlighted in bold. The pressure is known to drop for the crankshaft bearing depletion, lower gear oil pump efficiency, maladjustment of a pressure reducer in the oil line being of low probability, and other reasons.

As experiments showed, the useful life of all machinery parts is shortened during the machine performance due to cumulative fatigue damage of parts and joints. The fatigue damage is accumulated gradually and results in drift failure. The fatigue faults are linear and can be described with high probability by equation 1. The remaining useful life τ_o, in this case, is the difference between

Table 1. MTZ 82.1 tractor's technical condition values after 3950 operation hours.

Item No.	Diagnostic parameter	Nominal value	Limit value	Current value
1	Pressure in every tire, p_t ,kp/cm^2	0.15	0.09	0.15
2	Temperature of wheel-end bearings, $_{tb}$,°C*	–25…30	95	28
3	Pressure in the low-pressure fuel line, p_l, MPa	0.08	0.05	0.07
4	Pressure at the end of the compression stroke in the cylinder, p_i, MPa	9.0	4.5	7.5
5	Blow-by at 2100 min^{-1} G_r , L/min no more*	25	80	30
6	Dielectric capacity of engine oil, Z	2.5	2.3	1.5
7	Pressure in the main oil line at 2100 min^{-1}, p_m, MPa	3	1.5	1.4
8	Effective fuel consumption by an engine, g_e, g/kW·h**	220	234	224

*Measured regularly by a portable device; **found by remeasurement based on the known method (Gabitov *et al*., 2019).

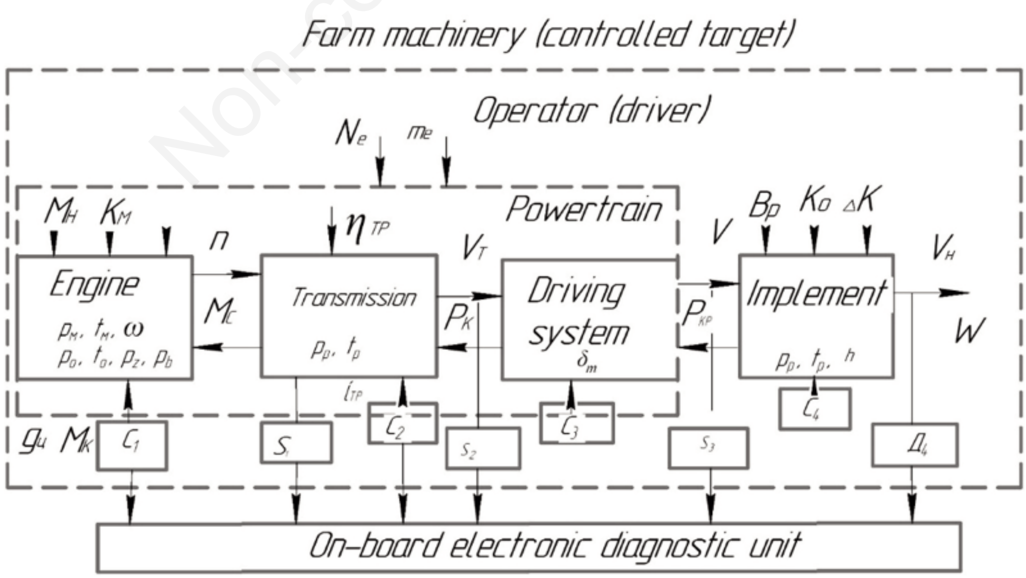

Figure 2. The CT's structural scheme, generalized: N_e - effective power, m_e - the specific effective fuel consumption, M_H - the torque, K_M - random parameter, g_z - is the cycle feed, p and t are the pressure and temperature of the measured media, respectively, ω - is the angular velocity, δ_m - is the slip coefficient, n - rotation frequency, $C_1…C_4$ - control signals, $S_1…S_4$ - signals from sensors, V - forward speed and other parameters.

prognosed operation until failure and the service time before the predicted period τ_i.

$$\tau_0 = \tau_{\text{пр}} - \tau_i, \tag{4}$$

This work offers to make calculations according to the minimum possible value of the remaining useful life $\tau_{p.s.}$ by the equation:

$$\tau_0 = \tau_i - \tau_{\text{p.m.}} \tag{5}$$

Let us consider this method as exemplified by pressure in the oil line p_l. For this purpose, the considered parameter gain that occurred during service is found through the equation (as in the graph of Figure 5):

$$\Delta p = \frac{p_i - p_l}{\tau_i} \tag{6}$$

Figure 3. The controlled target, tractor MTZ-82.1 'Belarus' with front-end loader 'Universal 800S', equipped with sensors-markers: 1- temperature and air pressure in tires 'TRV5'; 2- fuel pressure after a fine fuel filter 'MD-10'; 3- induction sensor 'SDS3'; 4- radio frequency identification (RFID) 'PR-G07'; 5- a driver availability monitoring 'MT-510'; 6- oil quality sensor 'QLT Sensor JM-4034'; 7- oil pressure sensor 'MD-12'; 8- differentiated fuel consumption meter 'DFM-220-A-P'; 9- acceleration indicator 'REF TEK147'; 10- air filter dirt indicator 'DC4'; 11- engine rotation frequency sensor with 'PKE key.

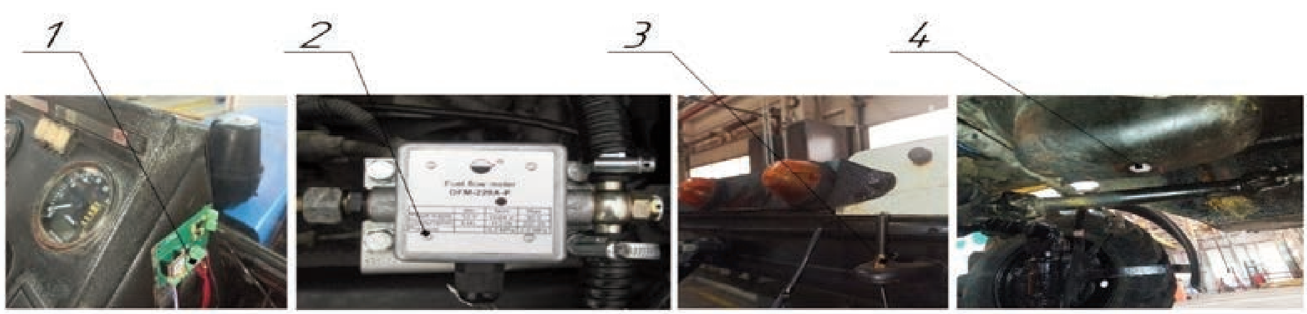

Figure 4. Disposition of the sensors (A-D) in the tractor: 1) a developed electronic unit with a digital interface for data collection and transmission; 2) a fuel consumption meter 'DFM-220-A-P'; 3) a GSM- tracker; 4) an oil quality sensor 'QLT Sensor JM-4034'.

where p_i is initial pressure for the studied period, MPa;
p_i=2.08 MPa;
p_l- limiting pressure for the studied period, MPa;
p_l=1.5 MPa;
τ_i=3540 operation hours for limiting pressure.

Then Δp=(2080000-1500000)/3540=163.841 Pa/1 operation hour.

Hence, based on the regularity (Dorokhov, 2010), there is an equation for changes of the considered parameter, that is oil pressure p_m:

$$p_m(\tau)=2.08-0.163841\cdot\tau, \tag{7}$$

Then the root-mean-square deviation of service hours σ_τ are as follows:

$$\sigma_\tau=\sqrt{\frac{\sum_1^n(\tau_i-\tau_{p.av.})}{n-1}}=\sqrt{\frac{43739704}{50-1}}=944.8 \text{ operation hours.} \tag{8}$$

Student's coefficient at the confidence factor *p=0.8* and the degree of freedom *N=2* equals τ(p)=1.29. The lowest confidence value $_{p.av.}$ for tractor's service hours until the lubrication system: $\tau_{p.m.}=\tau_{p.av}-\tau(p)\cdot\sigma_\tau$= 6018-1.29·944.8=4799 operation hours.

The schematic interpretation of the remaining useful life for the lubrication system is presented in Figure 5.

The minimum possible useful life of the lubrication system according to the minimum possible value of the remaining useful life of the tractor $\tau_{p.m}$ based on equation 5 is: τ_o=6018-4799=1219 operation hours.

The developed program (Insafuddinov *et al*., 2013) calculates the predicted amount of days until the prognosed failure of the most vulnerable node. The remaining useful life of other systems, found in the same way, is presented in Table 2.

The conducted examinations resulted in: i) a set of diagnostic parameters for machine units and systems; ii) statistical examination data and the way deviations in controlled parameters from standard values affect the performance efficiency and fuel consumption; iii) established predicted useful life, the date of failure, and the need to maintain particular nodes.

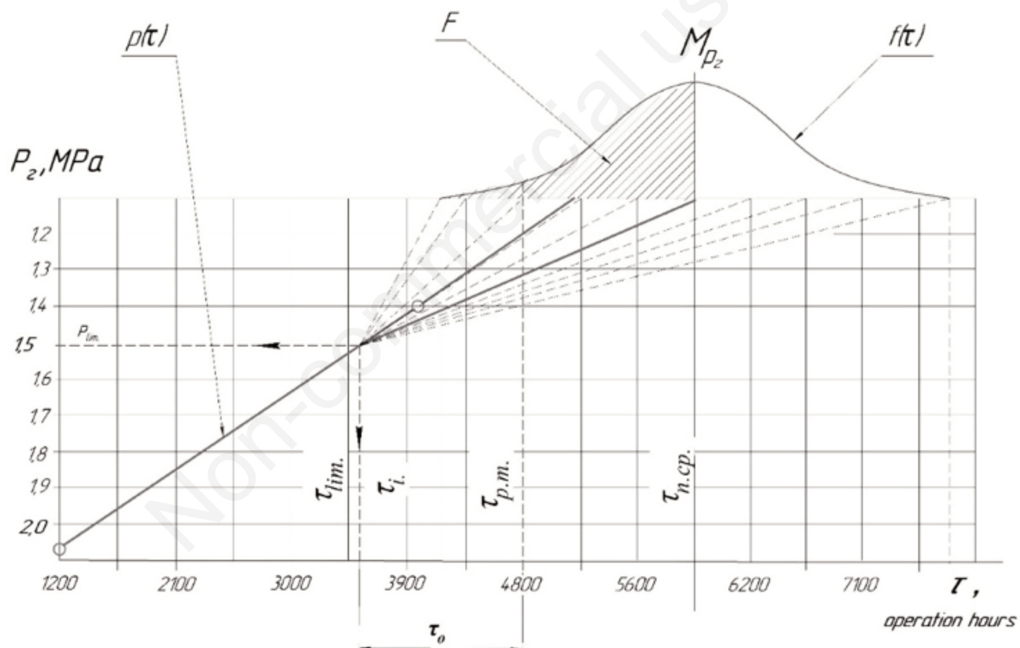

Figure 5. The graph to determine the remaining useful life τ_o of the tractor MTZ-82.1's lubrication system: *f(τ)* - a differential function of the standard distribution of possible failure; *F* - life length until the limiting condition; $\tau_{p.av.}$ - the possible average value of the remaining useful life; $\tau_{p.m.}$ - the minimum possible value of the remaining useful life; τ_i - current life length; τ_l - limiting life length.

Table 2. Calculated forecast values of the remaining lifetime of individual systems.

Item No.	The analysed system	The remaining lifetime, operation hours	The number of days before the failure at the current workload, days
1	The drive system	5822	346
2	The fuel system	2560	151
3	The connecting rod and piston group	2550	150
6	Lubricants	1219	71

Conclusions

One of the most crucial challenges in better maintenance and repair of farm machinery is evaluating their technical condition and the remaining lifetime.

According to the minimum possible value, detecting the remaining useful life makes it possible to calculate successful operation hours of the machine's systems with specified probability and provide technical diagnostics remotely based on the machine's current operating conditions according to the prognosed data.

The offered device with bundled software provides an automated evaluation of farm machinery's technical condition during their performance, calculate the remaining life length by condition diagnostics results.

Together with the device working in the net of info-communication technologies, the considered method helps increase farm machinery performance and reduce operating costs due to prevented expensive failures, individual prognostics, and operating machines' maintenance planning.

The proposed diagnostic model and a device for assessing and predicting the technical state of agricultural machinery in operational conditions is efficient and requires further field tests on other types of equipment during soil cultivation and harvesting to identify patterns of malfunctioning in unexplored units of mechanisms.

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