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Professional paper

IMPROVEMENT OF BUSINESS OPERATIONS THROUGH PHASES OF TECHNOLOGY DEVELOPMENT FOR MONITORING WELL PARAMETERS

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Abstract: The subject of the paper is a comparative analysis of technologies for monitoring well parameters through three phases of development. The research is based on a case study conducted on an oil field with 152 wells in Serbia. The aim of the study is to determine the impact of digitalization and wireless data transmission on operational efficiency and reduction of production costs. The methodology includes analysis of operational data collected during years of field work, including parameters such as number of operators, response time, and logistics requirements. Results show that the transition from manual data recording to real-time systems reduces the number of required operators by 83 percent. The total response time to changes in well operation was reduced from more than seven days in the paper phase, through two to three days in the digitalization phase, to 30 seconds in the real time phase. Analysis of logistics parameters indicates a reduction in daily vehicle mileage from 230 to 14 kilometers, accompanied by a 94 percent decrease in CO2 emissions. The paper also identifies limitations regarding data resolution and the influence of human factors on the speed of implementation of new solutions. The findings confirm the economic and environmental justification of introducing modern measurement systems in the oil industry. Identified intermediate phases point to the need for gradual adaptation of work processes to new technologies. The obtained data serve as a basis for future research in predictive maintenance and application of artificial intelligence algorithms in oil exploitation.

Keywords: Oil Industry, Well Monitoring, Digital Transformation, Real-Time Data Transmission, Case Study, Operational Efficiency, Oil Production Optimization

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1 INTRODUCTION

The issue of monitoring well parameters has been studied through different periods of technology development in oil production. A comparative analysis of the history of monitoring technologies was conducted based on available literature and practice. The analysis focused on operational data from the oil industry in Serbia. The topic was chosen due to its relevance and the limited number of studies based on long-term field data. The research is structured around phases identified through direct observation and work with equipment in the field. Each phase reflects real working conditions in a company operating 152 wells. The methodology was determined by technical specifications of instruments and machines used in different phases of exploitation, as well as the method of data transfer and processing. This approach allowed theoretical models to be tested through direct interaction with technology.

Data obtained reflect actual field conditions. Historical boundaries were set based on industry experience. These experiential data made it possible to identify turning points in operational processes that are not always visible in general scientific presentations. Each period reflects cycles in which changes in work methods and adoption of new solutions occurred.

Technology development is observed in historical context to explain how technical innovations influenced business processes. Each new phase brought changes in efficiency and speed of work. Analysis of these changes provides insight into how modernization of equipment reduced costs and increased output. The historical overview includes the transition from manual measurement methods to automated systems, which changed the structure of field work. The connection between technological progress and production optimization is the central part of the paper. Business improvement is considered a consequence of introducing solutions that changed resource management. Through analysis of practical examples, the paper shows how attitudes toward technology evolved and how its use led to more stable models of work in the oil industry. Technology is considered a tool that determines productivity level and precision of resource monitoring.

Parameters such as time, number of operators, vehicle mileage, and number of measurements were used in the study. These parameters changed during each phase, and the changes were used to analyze the justification of introducing new technologies in production. The following chapters present results of similar studies from scientific sources, a review of applied monitoring technologies, and comparison of their effects based on collected field data.

2 RELATED WORK

Oil exploitation using sucker rod pumps is a common artificial lift method that requires precise monitoring to maintain optimal production. Diagnostics of these systems went through a development process that in early phases relied on mechanical laws of physics without microprocessor processing. The so-called paper phase involved use of explosive sonologs and mechanical dynamographs that converted tensile force into physical displacement of a pen on paper (Gibbs, 1982; Gibbs, 1963).

Traditional systems showed shortcomings due to subjectivity in data interpretation and safety risks related to use of explosives at the wellhead. A major problem was delay of information, where several days could pass between occurrence of a failure and notification of engineers, causing production losses (Clegg et al., 1993; J. N. McCoy et al., 1988).

Digitalization, initiated by introduction of electronic load cells, enabled high-frequency data collection and identification of material fatigue not visible with previous methods. Modern online transmission and SCADA analytics allow visualization of processes in real time, reducing response time to less than one minute (Gibbs, 1987; Danylenko & Sotnik, 2025).

The study analyzes three phases on a sample of 152 wells, focusing on optimization of human resources, reduction of operational costs, and application of predictive maintenance for long-term sustainability of the oil industry. Maintenance is divided into reactive, planned, and predictive. Reactive repairs are performed after failure, planned inspections follow fixed schedules, and predictive models use sensor signal analysis to forecast equipment failure. This approach reduces unplanned downtime and ensures stability of production processes (Liang et al., 2024; Meddaoui et al., 2023; Jankov et al., 2026).

SCADA systems of the fourth generation enable real-time information processing. Integration of Internet of Things into oil systems provides precise monitoring of mechanical and electrical parameters (Vani et al., 2024; Danylenko & Sotnik, 2025). These systems use software algorithms for automatic alarm management and equipment diagnostics. Digital solutions allow remote monitoring of sucker rod pumps and other well equipment (Osaretin, 2025; Godase, 2025).

Remote monitoring reduces need for frequent field visits by operators. Fewer interventions lower vehicle mileage and fuel consumption. Reduced wear of vehicles decreases overall company costs (Novaković et al., 2025). This organization allows control of more production units with fewer field staff (Snytko et al., 2025; Liang et al., 2024).

Sensor data analysis enables early identification of failures. Continuous monitoring of load trends and motor electrical values helps detect system degradation. Predictive maintenance is based on statistical methods and probability models of failure (Novaković et al., 2025). These models support planning of interventions only when data show actual technical need. Effective prediction of downtime reduces spare part and overhaul costs (Liang et al., 2024; Meddaoui et al., 2023; Tian et al., 2021; Osaretin, 2025).

Machine learning algorithms are applied to large sets of historical data in the oil sector. Optimization of system operation is achieved through metaheuristic methods that improve energy efficiency (Marković et al., 2025). Timely action based on predictive indicators leads to higher profitability (Liang et al., 2024); (Ucar et al., 2024). Integration of artificial intelligence into control systems reduces risk of human error in decision making. Timely maintenance preserves equipment integrity and extends system life (Çınar et al., 2020); (Aderamo et al., 2024).

3 METHODOLOGY

The methodology is based on historical-comparative method and case study covering 152 wells. Field work and case study led to division of research into phases: paper phase, digitalization phase, and real-time data transmission phase. These phases were applied in practice of monitoring well parameters. Recognition and definition of phases were based on practice, and each new phase brought changes in oil production. Three phases were classified into periods: from mid-20th century to 1990s, from 1990s to 2020, and after 2020.

The criteria used to define each phase were based on the dominant diagnostic technology applied in the field (mechanical instruments in the paper phase, portable electronic devices in the digitalization phase, and permanently installed sensors with wireless transmission in the real-time phase). The data cover the period from the mid-20th century to the 2020s, with continuous records from 152 wells in Serbia. All wells were analyzed using the same methodological approach, with parameters including number of operators, response time, vehicle mileage, and measurement frequency. Reported values represent directly measured field data, aggregated into averages for each phase to ensure comparability.

The first period was characterized by use of mechanical dynamographs and explosive sonologs during direct field visits. Data were recorded on paper, and processing required manual counting of couplings and use of planimeter for calculation of power. Traditional systems carried safety risks due to use of explosives in flammable environments and work near moving parts of pump units (J. N. McCoy et al., 1988; Gibbs, 1963). Information delays of several days caused production losses. The second phase introduced electronic load cells that enabled high-frequency data collection (Gibbs, 1987; Clegg et al., 1993). Digitalization reduced human factor influence but still required operator presence to collect files. Portable units shortened reaction time compared to paper methods. The third phase involved permanently installed sensors and wireless real-time data transmission (Danylenko & Sotnik, 2025; Takacs & Kis, 2021).

Modern maintenance integrates artificial intelligence to predict system condition. Machine learning algorithms analyze sensor signals and identify wear patterns (Ucar et al., 2024; Vani et al., 2024). Deep learning methods allow automatic diagnostics of well operating states based on field data. Integration of product quality parameters into maintenance models influences reliability of the process. These systems reduce unplanned downtime and optimize operating costs. Use of artificial intelligence is considered a fourth phase of technology development for data transmission and predictive maintenance (Riccio et al., 2024; (Wang et al., 2021).

Each phase was followed by selection of device characteristics and parameters, allowing monitoring of technology development and production changes. Field measurements showed that data transmission and physical characteristics of instruments directly influence work processes. Comparison of characteristics showed that instruments became more adapted to operators over time. Reduction in instrument weight made use easier, reduced installation time, and lowered number of operators needed. For each instrument, characteristics were presented in tables to show innovation flow and impact on field processes.

Results indicate existence of intermediate phases between main periods, caused by lack of trust in new technologies. These transitional periods were marked by attempts of operators and engineers to control new systems while still relying on old equipment. Adaptation to new solutions was accompanied by resistance due to fear of job loss and reduced importance of their role. The intermediate phase between the first and second phases occurred gradually, with partial modifications of devices. The third phase was introduced quickly through investment in modern equipment. However, resistance was still present, with operators trying to prove malfunction of new equipment. This resistance was based on fear of innovation, doubts about the ability to operate new systems, and concerns about job security. These transitional phases were noted during direct field work and may serve as a basis for future studies. The authors did not conduct a separate analysis of them in this paper.

4 THE PAPER PHASE

The paper phase, covering the mid-20th century to the 1990s, was characterized by diagnostic methods based on mechanical physics and chemical reactions without microprocessor technology. Monitoring was periodic, with mechanical dynamographs placed directly on the polished rod. A system of springs and levers transformed tensile force into mechanical displacement of a pen that drew a force-stroke diagram on paper (Gibbs, 1963).

At the same time, explosive sonologs were used to determine fluid level. The process involved activating a charge in the annulus of the well, generating a sound wave. The echo reflected from couplings and fluid surface was recorded by a mechanical printer.

Depth was determined manually by counting amplitudes with a ruler (J. N. McCoy et al., 1988).

These methods were considered standard at the time due to robustness and independence from electrical power, which allowed stable operation in extreme conditions (Gibbs, 1992). Paper records provided permanent evidence without risk of software errors (Nicol & Purcupile, 1984). Manual data processing supported development of engineering intuition, enabling experts to identify valve irregularities by visual analysis of curve shape. The explosive impulse provided strong penetration of sound waves in deep wells (J. McCoy et al., 1997).

From today's perspective, these methods had significant shortcomings (Clegg et al., 1993). Subjectivity in interpretation and use of planimeters for manual measurement led to errors. Safety risks were present due to explosives in flammable environments and work near moving parts. Information delays caused production losses. Archiving paper documentation prevented long-term statistical analysis, while low resolution concealed early material fatigue.

Diagnostics in this phase included planimeter use, which connected mechanical records with mathematical calculation of power. After drawing the curve, engineers used a planimeter to determine surface area of irregular shapes. The measured area represented work performed during one cycle. Power was calculated using a formula with device constants(Garrett et al., 1996; Takacs, 2015).

The obtained area represented the work performed during one cycle. To calculate the power, a formula was used that included device constants (Takacs & Kis, 2021)

$$P = \frac{A * S * C * N}{K} \tag{1}$$

Where:
P - Power (kW)
A - Area measured by planimeter (cm2)
S – Spring scale (kg/mm)
C - Constant of pen stroke
N - Number of strokes per minute (min^{-1})
K - Conversion factor (6116 for kW).

Figure 1 shows the dynamograph used during the paper phase, while Table 1 presents the technical characteristics of the DYN 77 dynamograph.

Figure 1 Mechanical dynamograph with a paper display of the dynamograph card (Dynamograph DYN 77 | Sonoecho™, n.d.)

Table 1 Technical Specifications of the Dynamograph DYN 77

Characteristic	Description
Max. load:	140 kN / 14.5 t / 31,000 lbs
Max. stroke:	1 to 8 m (39 to 315")
Min. distance between bridels:	190 mm (7 1/2")
Weight	9.1 kg (20.0 lbs)

Figure 2 shows the sonolog used during the paper phase.

Figure 2 Powder-actuated Sonolog Model M (Echometer Model M Strip Chart Recorder - UPC Global, n.d.)

Table 2 presents the technical characteristics of the Sonolog Model M.

Table 2 Technical characteristics of the Sonolog Model M

Characteristic	Description
Enclosure / Housing	Compact plastic case
Cables	1.5 m cable for microphone and amplifier, 12 VDC car cigarette lighter cable
Power Supply	110/220 VAC automatic battery charger
Accessories	11-point divider, 10 paper rolls
Measurement Equipment	200 PSI gauge with quick connector
Spare Parts	O-ring set and small parts
Gas Cylinder	2.2kg cylinder for CO2 or nitrogen
Gas Accessories	Hose and cylinder charging connector

The plastic enclosure contains cable for connecting the microphone and amplifier. The device features an automatic battery charger supporting 110 or 220 volts, as well as a 12-volt power cable for a car cigarette lighter socket.

The package includes a divider, paper rolls, and a pressure gaugewith a quick connector. A set of O-rings and related parts are provided with the equipment. The standard offering includes a 2.2 kg cylinder for CO2 or nitrogen, unless otherwise specified. A hose and a cylinder charging connector are part of the standard equipment.

5 DIGITALIZATION PHASE

The digitalization phase, from the mid-1990s to early 2010s, marked transition from paper systems to semiconductor memory. Mechanical dynamographs were replaced by electronic load cells. Instead of mechanical pen movement, force on the polished rod changed electrical resistance in strain gauges, allowing high-frequency sampling and detection of vibrations not previously visible (Gibbs, 1987).

Explosives in sonologs were replaced by compressed gas, while microphones sent signals to processors that identified pipe couplings (J. McCoy et al., 1999). Despite digitalization, data transfer still required operator presence. Information was stored in device memory, and operators had to visit wells to collect data and manually upload them. Advantages included automatic calculation of diagram area with high precision, eliminating human error (Takacs, 2015). Archiving in digital databases allowed comparison of current and historical diagrams. Limitations included reactive maintenance, since data represented only snapshots. High operational costs and traffic risks from frequent visits remained (Lea & Bowen, 1992).

Technological basis included digital sonologs and dynamographs integrated into portable units. Compressed gas provided cleaner acoustic impulses, while digital signal processing enabled automatic recognition of well elements and reduced depth calculation errors (Gibbs, 1987). Software solutions enabled integration of collected data into simulation models, optimizing pump strokes and improving energy efficiency (Al Mubarak, 2022).

Figure 3 shows the Echometer Well Analyzer, while Figure 4 presents the sonolog and dynamograph used during the digitization phase

Figure 3. - Echometer Well Analyzer (Echometer Resigned, n.d.)

Figure 4 Digital sonolog and dynamograph (Echometer Resigned, n.d.)

Table 3 presents the technical characteristics of the digital sonolog, while Table 4 presents the technical characteristics of the digital dynamograph.

Table 3 Technical Characteristics of the Digital Sonolog

	Characteristic	Description
1	Working Pressure	Rated at 1500 psi
2	Microphone	Dual-disk, noise-canceling model
3	Pressure Gauge	1500 psi capacity
4	Dimensions	7.6 x 11.4 x 30.5 cm (3 x 4.5 x 12 in)
5	Weight	3.6 kg (8 lbs)

The device has a working pressure of 1500 psi and is equipped with a dual-disk noise-canceling microphone. The built-in pressure gauge also supports values up to 1500 psi.

Table 4 Technical Characteristics of the Digital Dynamograph

	Characteristic	Description
1	Installation	Between the pumping unit carrier bar and the polished rod clamp
2	Maintenance	No routine maintenance required
3	Data Processing	Uses Well Analyzer software
4	Calibration	Field recalibration possible
5	Sensors	Internal accelerometer
6	Throat / Opening	1.5 inc
7	Capacity	Rated up to 13600 lbs (30000 kg)

The device is installed between the pumping unit carrier bar and the polished rod clamp. The design requires no routine maintenance during operation. Data from the device is processed via the Well Analyzer, which analyzes collected information through integrated software. Measurement accuracy can be adjusted by field recalibration. The dynamograph features an internal accelerometer and a 1,5 in throat. The maximum rated capacity is 13,600 kg (30,000 lbs)

6 REAL-TIME DATA TRANSMISSION PHASE

The phase of real-time data transmission in the Serbian oil industry appeared during the 2020s. In this development stage, sensors that were previously used as portable devices became fixed and permanently installed on each individual well. Collected data were no longer stored locally but transmitted through wireless networks such as GPRS, radio links, or satellite terminals directly to a central server. The process of transmitting information from the well to the user within the SCADA system took place through three hierarchical levels.

The first level included the field part and direct acquisition of data from the well. Key components consisted of pump unit controllers and intelligent control stations that collected signals from permanently installed load cells and position sensors based on the Hall effect (Liang et al., 2024); Yadav & Paul, 2021). At this level, primary signal processing was carried out and motor operation was optimized by applying frequency converters (Ogunmesa, 2021).

The second level represented the communication bridge between field units and the control center. Data from controllers were transmitted through routers and wireless technologies to programmable logic controllers and central servers (Liang et al., 2024; (Yadav & Paul, 2021). This segment ensured the integrity of information and its distribution in real time (Wali & Alshehry, 2024).

The third level included the management and analytical segment where visualization was performed within the SCADA system. At this level, automatic analysis of diagram overlaps, alarm management, and processing of large data sets were carried out, which enabled the transition to predictive maintenance (Danylenko & Sotnik, 2025). The architecture of the described intelligent management system (Figure 5) was presented in the corresponding illustration (Jankov et al., 2025).

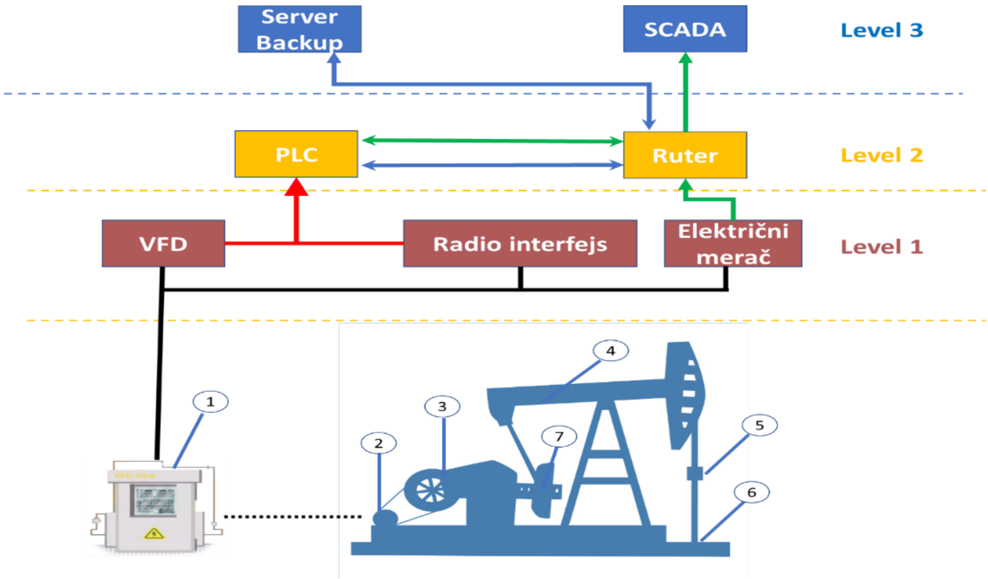

Figure 5 Data transfer from the well to the user (SCADA), (1-Intelligent Control Station (ISU), 2-electromotor, 3-gearbox, 4-balance beam, 5-dynamograph, 6-sonologist, 7-weights)

AVEVA[1] (https://www.aveva.com) develops software solutions that support and implement SCADA (Supervisory Control and Data Acquisition) systems through tools for process management, visualization, and data analysis. These solutions enable users to monitor and optimize industrial processes in real time, including direct integration with PLC and RTU devices. The AVEVA platform serves as a foundation for managing physical systems, providing the necessary infrastructure for operational oversight. The system is applied for process visualization, allowing specialists to respond to emergency situations.

Figure 6 shows the data collected from sensors which, following the described transmission, are used for analysis and decision-making. The interface displays well operating parameters in real time, allowing for the early detection of irregularities and providing the necessary time for their resolution

[1] A British multinational information technology consulting company headquartered in Cambridge. (AVEVA - Global Leader in Industrial Software).

Figure 6 Visualization of operating parameters in the AVEVA environment

The user could select the desired time interval for monitoring, with access to all historical data stored since the beginning of system use. Each parameter was analyzed individually, and due to the large amount of data, the system detected anomalies and predicted failure time. The intelligent management system automatically reported irregularities, after which specialists sent service requests before downtime occurred (Jankov et al., 2025).

In practice, sensor signals are acquired continuously, typically at intervals of 1 to 5 seconds depending on the parameter (load, stroke position, motor current). These raw data streams are locally processed and aggregated before transmission to the SCADA server. Due to memory and bandwidth limitations of the installed system, the SCADA platform does not store every single raw sample but instead updates the operator interface in a refresh cycle of approximately 30 seconds. This refresh interval therefore refers to the visualization layer, while the underlying acquisition occurs in much shorter intervals. At present, the 30 second cycle is a limitation of the installed system, and it represents a clear area for future improvement. Reducing the refresh interval in subsequent generations of SCADA platforms would provide additional benefits, including faster anomaly detection, more precise predictive maintenance, and improved operational efficiency.

There are many manufacturers of stationary sensors, which are mandatory in the third phase. One of them is Magmatek (https://www.mgtcontrol.ru), and their devices were used as an example for the description of the third phase.

For recording the dynamic level in this study, a stationary sonolog was used that records the level four times per day, with the option to adjust for a higher number of recordings. The sonolog also has the capability to measure and transmit data on pressure in the annular space. The manufacturer of the sonolog MGT APDU-1 is Magmatek, shown in Figure 7. The operation of the sonolog and the measurement of the level are presented in more detail in the referenced work (Jankov et al., 2025).

Figure 7 Sonolog MGT APDU-1 – stationary level meter in the annular space of the well (Приборы Контроля Параметров Скважин От Компании Магматэк, n.d.)

Table 5 presents the technical characteristics of the stationary sonolog, and Table 6 presents the technical characteristics of the stationary dynamograph.

Table 5 Technical characteristics of the stationary sonolog

	Characteristic	Description
1	Level measurement range	20 to 6,000 m
2	Level resolution	1 m or less
3	Pressure measurement range	0 to 100 kg/cm²
4	Pressure resolution	0.1 kg/cm²
5	Operating pressure	0.8 to 50 kg/cm²
6	Battery capacity	At least 4,000 measurements without charging
7	Charging time	Up to 3 hours
8	Communication	Bluetooth LE with NFC pairing
9	Communication range	30 m or more
10	Operating temperature	Between -40 and +50 °C
11	Service life	5 years or longer

In Figure 8, a dynamograph manufactured by Magmatek is shown, which is used as a stationary sensor.

Figure 8 Dynamograph MGT SDD-1 – stationary load meter of the sucker rod (Приборы Контроля Параметров Скважин От Компании Магматэк, n.d.)

Table 6 Technical characteristics of the stationary dynamograph

	Characteristic	Description
1	Measured load range	0 to 10,000 kgf
2	Measured stroke range	0 to 20 m (at 0.5 to 12 strokes/min)
3	Load measurement accuracy	≤1% full range
4	Load resolution	≤0.1% full range
5	Operation time (recording)	≥100 h
6	Power supply	Maintenance-free integrated battery
7	Communication channel	Bluetooth LE 4.x
8	Communication range	≥30 m
9	Setup method	NFC
10	Operating temperature	-40 to +50 °C
11	Calibration frequency	1 year
12	Service life	≥5 years
13	Weight	≤1.2 kg

7 RESULTS AND DISCUSSION

The results will be presented through analysis of each individual phase, as well as through comparative tables and diagrams. Data were collected from five measurements of each well per month, which is a total of 760 measurements for 152 wells.

The comparative results presented in Tables 7–10 confirm that the overall response time decreased from more than seven days in the paper phase to 30 seconds in the real time phase. It should be emphasized that the 30 second value refers to the refresh cycle of the SCADA visualization system, while the actual sensor acquisition occurs in much shorter intervals (1–5 seconds). This distinction highlights both the current limitation of the installed system and the potential for further improvement. Future upgrades aimed at reducing the refresh cycle would provide additional benefits in terms of faster anomaly detection and enhanced predictive maintenance.

7.1 Parameters of the first phase

In the first development phase, operational processes required significant time engagement due to the specifics of the mechanical instruments used. Work at the well site included installation of a massive mechanical dynamograph, preparation of the drum with a paper card, activation of the explosive charge, and manual reading of the record on the paper strip, which on average lasted 60 minutes. Transport and logistics required an additional 60 minutes due to the condition of road infrastructure and the need for regular maintenance of measuring devices, including cleaning of combustion residues from the explosive charge.

The key difference compared to later phases was in the process of data processing in the office, which required 30 minutes per well. Measurement results were not immediately available, and technical staff had to use a planimeter for manual calculation of the surface area of each individual chart. The total time required to process one recording was 150 minutes.

When calculating daily capacity within a 12-hour shift, taking into account effective working time of 10.5 hours after preparation of materials and servicing of instruments, a defined formula was applied for calculating operational output.

$$\frac{10{,}5\ hours}{2{,}5\ hours\ per\ well} = 4{,}2\ measurements\ per\ day\ per\ operator \tag{2}$$

The capacity of an operator (15 working days) was calculated using Formula 3.

Monthly

$$15\ days\ x\ 4{,}2\frac{measurements}{day} = 63\ measurements\ per\ month\ per\ operator \tag{3}$$

The required number of operators for 760 measurements is given by Formula 4.

$$\frac{760\ total\ measurements}{63\ measurements\ per\ operator} = 12{,}06\ operators \tag{4}$$

7.2 Parameters of the second phase

In the digitalization phase, operational processes required less time engagement compared to the previous period, but physical presence at the site still remained a key factor. Work at the well included installation of the digital dynamograph and sonolog, their connection to the computer unit via cables, as well as data reading, which on average lasted 30 minutes. Transport and logistics required an additional 45 minutes due to the specifics of road infrastructure and the spatial distance between individual wells.

Data processing in the office lasted 15 minutes per recording. Although the data were collected in digital format, it was still necessary to allocate time for synchronization with the central database and for final validation of the results. The total time required for complete processing of one recording amounted to 90 minutes. When calculating daily capacity within a 12-hour shift, taking into account effective working time of 10.5 hours after equipment preparation and instrument maintenance, a defined formula was applied to quantify operational output.

$$\frac{10{,}5\ hours}{1{,}5\ hours\ per\ operator} = 7\ measurements\ per\ day\ per\ operator \tag{5}$$

The capacity of an operator (15 working days) was calculated using Formula 36

Monthly

$$15\ days\ x\ 7\frac{measurements}{day} = 105 measurements\ per\ month\ per\ operator \tag{6}$$

The required number of operators for 760 measurements is given by Formula 7.

$$\frac{760\ total\ measurements}{105\ emasurements\ per\ operator} = 7{,}23 operators \tag{7}$$

For stable functioning of the system in the second phase (digital portable equipment), it is necessary to employ 8 operators (in order to cover deviations, equipment failures, and shift overlaps).

7.3 Parameters of the third phase

In this phase, the human factor in the measurement process was reduced to zero for routine checks. Sensors are fixed, and measurement is performed continuously (24/7) without human presence. The software (AVEVA/SCADA) automatically analyzes the chart. The engineer usually reacts only to an alarm (Jankov et al., 2025). One operator (dispatcher) can monitor all 152 wells in real time. The required number of operators in the field is drastically reduced, and they become exclusively an intervention team rather than a measurement team.

7.4 Comparative analysis of results

Comparative analysis of the number of operators

In Table 7, comparative data by phases are presented for the number of operators, time to information, measurement hours, and operator cost index.

Table 7 Comparative overview of exploitation efficiency for 152 wells

Parameter	Phase 1 (Paper)	Phase 2 (Digital)	Phase 3 (Online)
Required number of operators	12	8	1–2 (supervision)
Time to information	2–3 days	12–24 hours	30 seconds
Annual working hours (measurement)	22,800 h	13,680 h	~0 h
Labor cost (index)	100%	66%	<15%

The transition from the first to the third phase brings not only precision, but also frees up more than 80% of human resources that can be redirected to more complex engineering tasks. While in the first phase the focus was on data collection, in the third phase the focus is on optimization. The drastic reduction in response time (from several days to several minutes) directly prevents fluid losses caused by unnoticed failures, making the investment in the SCADA system pay off in record time.

Figure 9 presents graphical representation of the reduction in the number of required operators across the three phases, together with the reduction in response time for obtaining field information

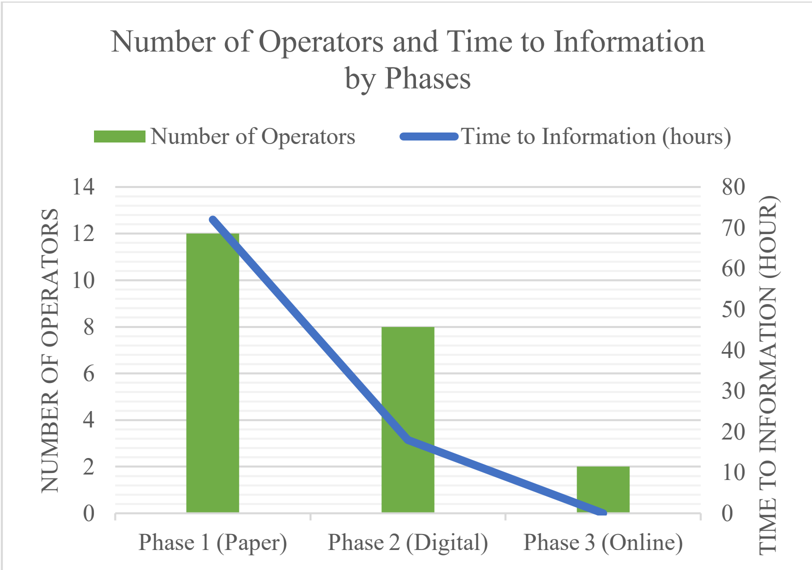

Figure 9 Graphical representation of the reduction in the number of required operators across the three phases, together with the reduction in response time for obtaining field information.

Comparative Overview of Response Time

Table 8 Comparative Overview of Response Time in Relation to Data Transmission Across Phases.

Table 8 Comparative Overview of Response Time from Failure to Information

Parameter	Phase 1 (Paper)	Phase 2 (Digital)	Phase 3 (Online)
Frequency of control	5 times per month	5 times per month	Continuous (24/7)
Failure detection time	5–7 days	2–3 days	30 seconds (Alarm)
Data processing time	30 min (Manual)	10 min (Software)	Instant (Automatic)
Total response time	7+ days	2–3 days	30 seconds

Economic Analysis

The economic feasibility analysis for the model of 152 wells is based on an average distance of 10 km between the locations and the base, with a unit transportation cost of 0.50 EUR per kilometer. In the first two development phases, which include manual and portable digital systems, each individual measurement requires a physical vehicle trip to the field. The calculation shows that with an annual intensity of 9,120 measurements, the total mileage reaches 91,200 km. This operational model generates annual transportation expenses of 45,600 EUR.

The transition to the third development phase, based on online data transmission systems, allows automation of the information collection process. Field activities in this model are carried out only upon detection of irregularities, applying the principle of management by exception. Statistical data show that, on average, 30% of wells per month require intervention, resulting in approximately 547 annual field trips. The annual mileage in this scenario amounts to 5,472 km, while the associated transportation costs are reduced to 2,736 EUR. The difference in costs indicates a high level of financial savings achieved through automated monitoring.

In this study, the analysis focused on transportation parameters and the reduction in the number of operators. The introduction of monitoring and remote-control systems, however, involves many additional aspects that need to be evaluated in order to provide a complete investment assessment and an approximate calculation of implementation profitability. The presented transportation savings represent only a part of the overall economic justification. A complete evaluation should also include capital expenditures (CAPEX), such as system investment cost, sensor installation, and software/communication infrastructure, as well as operational expenditures (OPEX) related to maintenance and data services. Preliminary estimates indicate that the reduction in manpower and logistics costs significantly offsets the initial investment, resulting in a positive return on investment (ROI) within the first years of system operation. A broader economic assessment, including CAPEX, OPEX, and ROI, will be addressed in future scientific works.

Reduction of CO_2 Emissions

The transition from manual monitoring (Phase 1/2) to online SCADA monitoring (Phase 3) across 152 wells reduces annual CO_2 emissions from 14,592 kg to 875 kg, representing a reduction of nearly 14 t (94%). This technological evolution directly contributes to ESG goals by lowering annual mileage from 91,200 km to 5,472 km, as shown in Table 10.

Table 10 Reduction of CO_2 Emissions in Phase 3 Compared to Phase 1

Parameter	Phase 1	Phase 3	Difference
Number of operators	12	2	−83%
Response time	7+ days	30 seconds	Reduced by >99%
Vehicle mileage	230 km/day	14 km/day	−94%
CO_2 emissions	High (baseline)	Reduced by 94%	−94%

Figure 10 shows a significant reduction of carbon dioxide emissions in the third phase compared to the first two. By eliminating routine manual inspections of 152 wells and applying the principle of management by exception, annual emissions are reduced from 14,592 kg to 875 kg. This reduction of 94%, amounting to approximately 14 tons annually, positions digital transformation as the primary tool for achieving environmental sustainability within the oil sector.

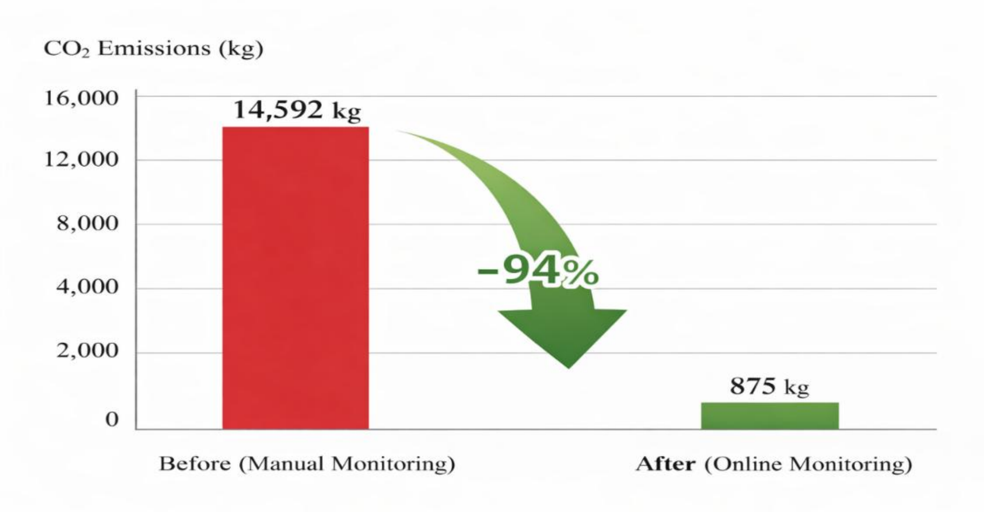

Figure 10 Comparative Display of Annual Emissions (kg) in the Field with 152 Wells Before and After Implementation of Online Monitoring

8 DISCUSSION

The comparative results presented in Tables 7 to 10 are based on directly measured field data from 152 wells, aggregated into averages for each phase. This approach ensures that the reported values reflect actual operational practice rather than estimates. The criteria for phase definition were consistent across all wells, and the same parameters (number of operators, response time, vehicle mileage, and measurement frequency) were applied uniformly. By presenting averaged values, the analysis highlights general trends while minimizing the influence of extreme individual cases.

The discussion of results connects the measured values with theoretical assumptions and previous research in the oil industry. The comparison of the three technological phases across 152 wells confirms that automation changes the structure of operational costs. The obtained data on the reduction of the number of operators by 83% correlate with the findings of the author (Gibbs, 1987) regarding the impact of electronic measuring cells on labor productivity.

The overall response time decreased from more than seven days in the paper phase, through two to three days in the digitalization phase, to 30 seconds in the real time phase represents a key change in production management. While traditional paper-based methods required manual processing and physical transfer of diagrams, the third phase enables immediate detection of irregularities in the operation of pumping units. Such results are consistent with research (Takacs & Kis, 2021) which emphasize the importance of real-time transmission for reducing fluid losses due to unplanned downtime.

Logistical parameters, such as the reduction of daily mileage from 230 km to 14 km, indicate a change in the maintenance model. The transition from reactive to predictive maintenance reduces the need for routine site visits. The results showing a 94% decrease in CO_2 emissions complement the techno-economic analysis with ecological indicators, which is consistent with modern requirements for sustainable oil exploitation. (Danylenko & Sotnik, 2025).

The observed limitations in data resolution of 30 seconds indicate the need for further refinement of compression algorithms. Although cloud analytics enables large-scale data processing, local recording still retains an advantage in diagnosing specific high-frequency dynamic processes. The discussion of these limitations opens space for the introduction of a fourth phase, which would employ deep learning methods for automatic interpretation of signals directly at the wellhead. (Ucar et al., 2024).

The identified intermediate phases and workforce resistance to new technologies confirm that technical solutions depend on the organization's readiness for change. Operators' fear of losing their role in the management process influences the speed of adoption of digital tools. This phenomenon requires further analysis from the perspective of engineering management in order to ensure full integration of modern systems into everyday field operations.

9 CONCLUSION

The research conducted on a sample of 152 wells confirms that technological development is fundamentally transforming operational processes within the oil industry. The transition from manual data recording to automated real-time systems has resulted in a significant reduction in the workforce, decreasing the number of operators from 12 to 2. This 83% reduction in human resource engagement is a direct consequence of implementing modern measuring instruments and cloud analytics, which minimize the need for a physical presence on-site for routine measurements.

An analysis of logistical parameters indicates a drastic drop in daily vehicle mileage from 230 to 14 kilometers. This reduction in transport activities has cut annual fuel and maintenance costs by over 90%. Simultaneously, a 94% decrease in CO_2 emissions was recorded, highlighting the environmental benefits of technological modernization. Furthermore, the results confirm that switching to wireless data transmission shortens the response time to operational changes from 48 hours to just 30 seconds.

However, certain research limitations remain, primarily regarding data transmission and resolution. The current 30-second refresh interval and cloud-based signal compression prevent the detection of specific high-frequency dynamic changes that are otherwise visible during local recording. Additionally, since the study was conducted on a specific oil field, variations in terrain and equipment age at other locations may affect the implementation speed of the third phase. Human resistance to new technologies also remains a limiting factor for total system automation.

Future work will focus on the fourth phase of development, involving the application of Artificial Intelligence (AI) and predictive maintenance. The primary focus will be the integration of deep learning algorithms to enable automated diagnostics without production downtime. Plans are also in place to examine increasing data resolution without straining network infrastructure. Further research will encompass a comprehensive analysis of the economic effects of full automation on the long-term stability of oil exploitation systems

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