

AN INTELLIGENT MODULE FOR PRODUCTIVITY ASSESSMENT OF REMOTE EMPLOYEES IN WORKING TIME MONITORING SYSTEMS

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Abstract. This paper presents the development of an intelligent module for a working time management and accounting system aimed at improving remote employee productivity analysis and decision support. The proposed module extends traditional time tracking functionality by integrating multicriteria productivity assessment, anomaly detection, short-term forecasting, and recommendation generation mechanisms. The developed approach combines an AHP-based productivity evaluation model, a hybrid anomaly detection algorithm using the Isolation Forest and statistical analysis, an LSTM-based forecasting model, and a fuzzy logic recommendation system. The developed methods were verified using a synthetic dataset containing 500 records. The obtained results confirmed the effectiveness of the proposed solution. The productivity assessment model demonstrated a strong correlation with expert evaluations ($r = 0.87$), while the anomaly detection and forecasting components showed satisfactory performance according to the selected evaluation metrics. The recommendation subsystem demonstrated practical applicability, with 78% of generated recommendations accepted by management personnel. The developed intelligent module provides an integrated approach to productivity analysis, detection of abnormal work patterns, forecasting of future performance, and support of managerial decision-making in remote workforce management systems.

Keywords: intelligent module, working time management system, remote employee productivity, anomaly detection, LSTM forecasting, fuzzy logic

INTELIGENTNY MODUŁ DO OCENY PRODUKTYWNOŚCI PRACOWNIKÓW ZDALNYCH W SYSTEMACH MONITOROWANIA CZASU PRACY

Streszczenie. W niniejszym artykule przedstawiono opracowanie inteligentnego modułu dla systemu zarządzania i rozliczania czasu pracy, mającego na celu usprawnienie analizy wydajności pracowników zdalnych oraz wsparcie procesu decyzyjnego. Proponowany moduł rozszerza tradycyjne funkcje rejestrowania czasu pracy poprzez integrację mechanizmów wielokryterialnej oceny wydajności, wykrywania anomalii, prognozowania krótkoterminowego oraz generowania rekomendacji. Opracowane podejście łączy model oceny wydajności oparty na metodzie AHP, hybrydowy algorytm wykrywania anomalii wykorzystujący metodę Isolation Forest oraz analizę statystyczną, model prognozowania oparty na sieci LSTM oraz system rekomendacji oparty na logice rozmytej. Opracowane metody zweryfikowano przy użyciu syntetycznego zbioru danych zawierającego 500 rekordów. Uzyskane wyniki potwierdziły skuteczność proponowanego rozwiązania. Model oceny wydajności wykazał silną korelację z ocenami ekspertów ($r = 0,87$), natomiast komponenty wykrywania anomalii i prognozowania osiągnęły zadowalające wyniki zgodnie z wybranymi wskaźnikami oceny. Podsystem rekomendacji wykazał praktyczną przydatność – 78% wygenerowanych rekomendacji zostało zaakceptowanych przez kadrę kierowniczą. Opracowany moduł inteligentny zapewnia zintegrowane podejście do analizy wydajności, wykrywania nietypowych wzorców pracy, prognozowania przyszłych wyników oraz wsparcia procesu podejmowania decyzji zarządczych w systemach zarządzania pracownikami zdalnymi.

Słowa kluczowe: moduł inteligentny, system zarządzania czasem pracy, wydajność pracowników pracujących zdalnie, wykrywanie anomalii, prognozowanie z wykorzystaniem sieci LSTM, logika rozmyta

Introduction

Digital transformation of organizations and the rapid development of information technologies have significantly changed traditional approaches to workforce management. In recent years, remote work has become an established form of employment rather than a temporary organizational measure. The transition to distributed teams has created new challenges related to monitoring work activity, evaluating employee performance, maintaining effective communication, and supporting managerial decision-making [7, 15].

Traditional working time accounting systems are primarily focused on recording attendance, duration of work, and compliance with established schedules. However, such approaches provide limited information about the actual effectiveness of employees, especially in remote environments where direct observation of work processes is impossible. Modern organizations require analytical tools capable of considering multiple aspects of professional activity, including task completion quality, communication behaviour, workload distribution, and changes in productivity over time [7, 17].

Existing studies demonstrate that productivity assessment in distributed teams requires the use of multicriteria approaches, since employee performance cannot be reliably characterized by a single indicator. Methods based on multi-criteria decision analysis provide the ability to combine heterogeneous performance factors and determine their relative importance through expert evaluation [14]. However, many existing approaches are limited to retrospective analysis and do not provide mechanisms for detecting abnormal behaviour patterns or predicting future productivity changes.

The application of artificial intelligence methods provides new opportunities for improving workforce analytics systems. Machine

learning algorithms can be used to identify deviations from typical work patterns, while neural network models allow forecasting future states based on historical activity data. In particular, anomaly detection methods based on Isolation Forest algorithms have demonstrated effectiveness in identifying irregular patterns in complex datasets [3, 10]. Recurrent neural networks, especially Long Short-Term Memory (LSTM) architectures, are widely used for sequential data analysis due to their ability to capture long-term dependencies [8, 9].

An important aspect of intelligent workforce management systems is not only analytical assessment but also the ability to support managerial decisions. The integration of fuzzy logic methods and expert knowledge allows the formation of adaptive recommendations considering both quantitative indicators and contextual factors. Such an approach corresponds to modern concepts of artificial intelligence-based decision support systems [11, 12, 13].

Existing intelligent workforce monitoring solutions typically implement only a limited subset of analytical functions [7, 15]. Most commercial and research systems focus either on time tracking and reporting, productivity visualization, or isolated applications of machine learning techniques [18, 19]. As a result, productivity assessment, anomaly detection, forecasting, and intelligent recommendation generation are usually implemented as independent components rather than as an integrated decision-support framework. This fragmentation limits the effectiveness of managerial decision-making and reduces the practical applicability of intelligent workforce monitoring systems in dynamic remote working environments.

Despite significant progress in individual areas, there remains a need for integrated solutions that combine productivity evaluation, anomaly detection, forecasting, and recommendation generation within a single software module. Therefore, the deve-

lopment of an intelligent component for working time management systems represents an important scientific and practical task.

The *aim* of this research is to develop an intelligent module for a working time management and accounting system that enhances traditional monitoring functionality through multicriteria productivity assessment, automatic anomaly detection, short-term forecasting, and intelligent decision support mechanisms.

1. Development of the productivity assessment model

A multicriteria approach was selected in the paper for evaluating the productivity of remote employees. The choice of this approach is justified by the need to consider various aspects of work activity under remote working conditions [14].

For the multicriteria approach, an integral mathematical model for productivity assessment was developed, which takes into account key work efficiency indicators:

$$P(t) = \alpha_1 \cdot T_{eff}(t) + \alpha_2 \cdot Q_{task}(t) + \alpha_3 \cdot C_{comm}(t) + \alpha_4 \cdot S_{sched}(t) \quad (1)$$

where $P(t)$ – the integral productivity indicator at time t ; $T_{eff}(t)$ – the coefficient of working time utilization efficiency; $Q_{task}(t)$ – the task completion quality indicator; $C_{comm}(t)$ – the communication activity index; $S_{sched}(t)$ – the work schedule adherence coefficient; $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ – weighting coefficients satisfying the condition: $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$.

The coefficient of working time utilization efficiency is calculated according to the following formula:

$$T_{eff}(t) = \frac{T_{work}(t) - T_{idle}(t)}{T_{norm}} \quad (2)$$

where $T_{work}(t)$ – the actual worked time according to the data from the working time accounting system; $T_{idle}(t)$ – idle time defined as periods of inactivity exceeding 15 minutes; T_{norm} – the standard working time for a specific position.

The task completion quality indicator is determined through the analysis of deadline adherence and the number of completed tasks:

$$Q_{task}(t) = \frac{N_{completed}(t)}{N_{assigned}(t)} \cdot \left(1 - \frac{D_{delay}(t)}{D_{total}(t)}\right) \quad (3)$$

The Analytic Hierarchy Process (AHP) method [3] is used to determine the optimal weighting coefficients, allowing expert assessments of the importance of various productivity criteria to be taken into account. The pairwise comparison matrix is formed based on surveys of managers and HR specialists of the organization.

The software implementation of the integral productivity indicator calculation was implemented in Python. As shown in Figure 1, the algorithm operates using two parallel processing streams. The first applies the Isolation Forest method [1, 6], while the second uses the statistical three-sigma rule:

$$Anomaly_Score(x) = 2 \frac{E(h(x))}{c(n)} \quad (4)$$

where:

$E(h(x))$ – the average path length for point x in the ensemble of isolation trees; $c(n) = 2H(n-1) - \frac{2(n-1)}{n}$ – the normalization coefficient; $H(i)$ – the i -th harmonic number;

$$Anomaly_Flag(t) = |P(t) - \mu_P| > 3\sigma_P \quad (5)$$

where μ_P and σ_P are the mean value and standard deviation of the productivity indicator calculated over the previous 30 working days.

A data point is considered anomalous if at least one of the methods indicates a deviation (the OR operator), which increases the detection completeness ($Recall = 0.873$) while maintaining accuracy ($Precision = 0.912$).

The anomaly detection algorithm was implemented as a software component combining the Isolation Forest method with statistical analysis based on the three-sigma rule. The module performs parallel analysis of productivity indicators and classifies observations as anomalous if at least one detection method identifies a significant deviation.

Experimental testing of the algorithm on synthetic data demonstrated an anomaly detection accuracy of 89.3% with a false positive rate of 4.7%.

A forecasting model based on a Long Short-Term Memory (LSTM) recurrent neural network was developed to predict future employee productivity. The choice of the LSTM architecture is justified by the ability of this type of neural network to effectively process sequential data and capture long-term dependencies [8, 9]. The architecture of the developed neural network is presented in Figure 2.

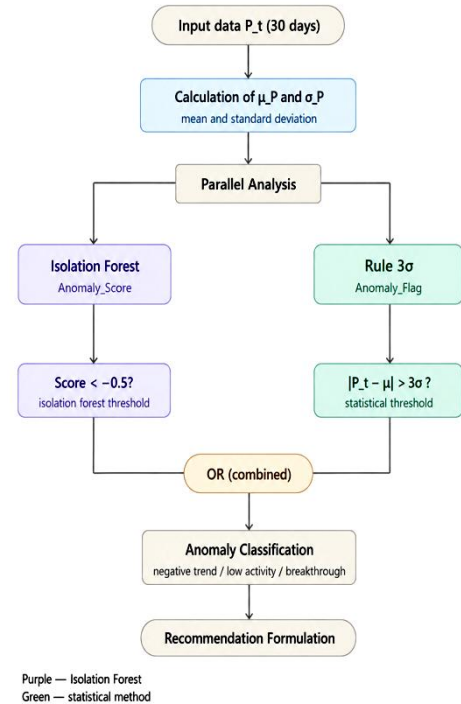


Fig. 1. Flowchart of the hybrid anomaly detection algorithm

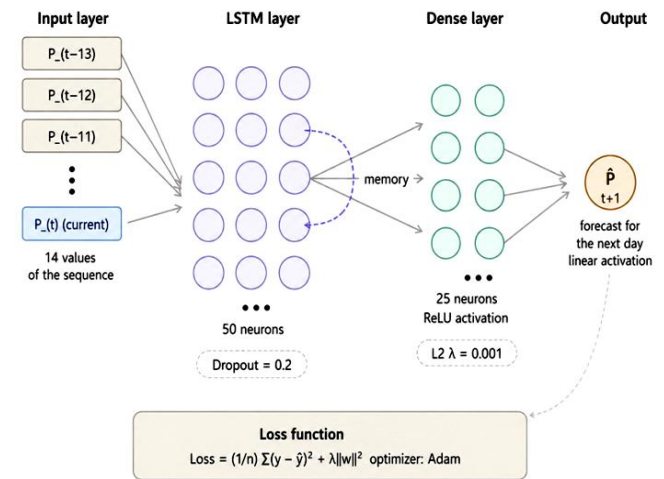


Fig. 2. Architecture of the LSTM neural network for productivity forecasting

As shown in Figure 2, the network consists of four sequential layers. The input layer receives a time series containing 14 values of $P(t)$. The LSTM layer (50 neurons) with dropout 0.2 is trained to detect long-term patterns in productivity dynamics. The Dense layer (25 neurons, ReLU activation function, L_2 regularization $\lambda = 0.001$) performs nonlinear feature transformation. The output neuron with linear activation generates the forecast value $P(t+1)$ for the next working day.

The loss function is defined as the mean squared error with L_2 regularization [19]:

$$Loss = \frac{1}{n} \cdot \sum (y_{actual} - y_{predicted})^2 + \lambda \cdot \sum w^2 \quad (6)$$

Based on the results of productivity analysis and detected anomalies, an expert system for generating recommendations for management personnel was developed. The system uses fuzzy logic rules to generate personalized recommendations aimed at optimizing work processes. The complete system algorithm – from the fuzzification of input variables to the defuzzification of the output recommendation is presented in Fig. 3 [12, 16]:

IF (Productivity = Low) AND (Trend = Declining), THEN
(Recommendation = "Critical intervention")

IF (Productivity = High) AND (Workload > Normal), THEN
(Recommendation = "Overload risk")

IF (Anomalies = Detected) AND (Type = "Irregular schedule"),
THEN (Recommendation = "Schedule adjustment")

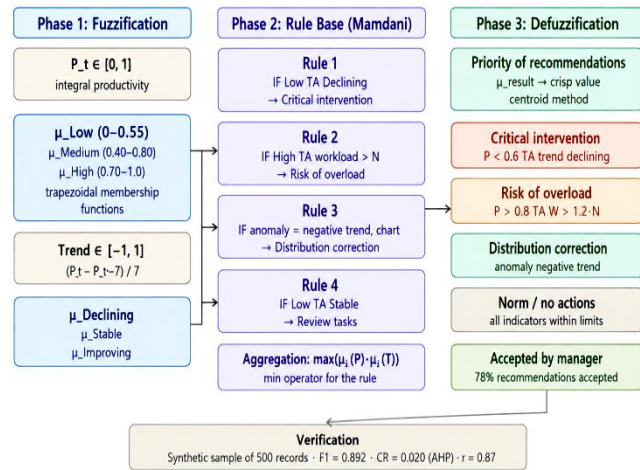


Fig. 3. Algorithm for generating recommendations based on fuzzy logic (Mamdani method)

The system operates in three phases. During the fuzzification stage, the crisp values $P(t)$ and Trend are transformed into membership degrees of linguistic terms (Low, Medium, High; Declining, Stable, Improving) using trapezoidal membership functions. During the rule base application stage, the minimum operator determines the activation degree of each rule, while the maximum operator aggregates the obtained results. During the defuzzification stage, the centroid method is used to obtain a crisp value representing the priority of one of the four recommendations [2, 10].

The recommendation system is integrated with all components of the intelligent module through unified interfaces, which ensures a comprehensive approach to situation analysis and the formation of well-grounded management decisions. The algorithm considers not only current productivity indicators but also historical trends, individual employee characteristics, and the context of performed tasks.

The effectiveness of the recommendation system is evaluated through the recommendation acceptance rate by managers and subsequent improvements in team productivity indicators. Preliminary testing demonstrated that 78% of generated recommendations were accepted for implementation by management personnel, indicating their practical value and validity.

2. Intelligent module architecture and implementation

The developed intelligent module for productivity analysis and forecasting represents an integrated system that organically extends the basic functionality of working time accounting with advanced decision-support capabilities. The mathematical models and algorithms described in this section provide automation of complex analytical processes and improve the quality of remote team management.

Figure 4 presents the structural diagram of the developed intelligent module and its integration into the overall system architecture [8, 13].

The UML class diagram of the intelligent module demonstrates the object-oriented architecture of the software implementation of the productivity analysis system. The central element of the architecture is the Intelligent Module interface, which defines a common contract for all components of the intelligent module and provides a unified approach to data processing.

The Data Collector class is responsible for collecting and preliminary processing of data from the main working time accounting system. It contains the methods collect time data (.), collect task data (.), and collect data (.), which provide the acquisition of various types of information about employee activity. The aggregate daily metrics (.) method performs the aggregation of collected data into daily indicators required for further analysis.

The Productivity Analyzer class is the key component for calculating the integrated productivity indicator according to formula (1). The class encapsulates the logic for calculating efficiency coefficients, task completion quality indicators, and other productivity-related components. The update weights (.) method provides adaptive adjustment of weighting coefficients based on feedback received from the system.

The Anomaly Detector class implements a hybrid anomaly detection algorithm that combines isolation forest methods and statistical analysis. The class includes methods for anomaly type classification and anomaly score calculation, enabling automatic identification of atypical patterns in employee work behaviour.

The Productivity Predictor class encapsulates an LSTM model for forecasting future productivity. The class provides data preparation in the form of time sequences, neural network training, and prediction generation. The save model(.) and evaluate model(.) methods ensure storage of the trained model and assessment of its performance quality.

The Recommendation Engine class implements an expert system for generating recommendations based on fuzzy logic. The class contains a rule base for different scenarios and methods for prioritizing recommendations depending on the severity of identified issues.

The Report Generator class is responsible for visualizing analysis results and generating reports for management personnel. The class provides the generation of various types of reports, including productivity reports, anomaly reports, prediction reports, and general dashboards.

The interaction between the classes is organized according to the principle of sequential data processing: Data Collector transfers processed data to Productivity Analyzer, which, in turn, provides calculation results to Anomaly Detector and Productivity Predictor. Recommendation Engine receives data from all analytical components and generates comprehensive recommendations, which are transferred to Report Generator for the preparation of final reports.

For this module, a UML class diagram was developed, presented in Figure 5, which demonstrates the object-oriented structure of the software implementation.

The next stage of the research involves the practical implementation of the designed system with the integration of the developed intelligent module, testing of functional capabilities, and evaluation of its effectiveness under real-world operating conditions.

Formula (1) includes four components T_{eff}^2 , Q_{task} , C_{comm} and S_{sclcd} . The components T_{eff} and Q_{task} are defined in formulas (2) and (3). To ensure the mathematical completeness of the model, the two components that were omitted in the previous description are formalized below.

The communication activity index C_{comm} reflects the intensity and quality of an employee's interaction with the team on day t and is defined by the following formula:

$$C_{comm,t} = \min \left(\left(\frac{M_t}{M_{norm}} \right) \cdot \beta_m + \left(\frac{R_t}{R_{norm}} \right) \cdot \beta_r, 1 \right) \quad (7)$$

where M_t – the number of initiated or processed messages on day t ; M_{norm} – the standard number of messages (the median

value for the team over the previous 30 days); R_t – the number of responses provided within the agreed SLA; R_{norm} – the standard number of timely responses; $\beta_m = 0.6$, $\beta_r = 0.4$ – the weighting coefficients of the communication components. The function $\min(\cdot, 1)$ limits the value of $C_{comm} \leq 1$, preventing distortion of the integral indicator caused by excessive communication activity.

The work schedule adherence coefficient S_{sclcd} characterizes the correspondence between the actual distribution of activity and the planned working time:

$$S_{sclcd,t} = 1 - \frac{|T_{start,t} - T_{sclcd}| + |T_{end,t} - T_{fin}|}{2 \cdot T_{norm}} \quad (8)$$

where $T_{start,t}$ – the actual time of the first recorded activity;

T_{sclcd} – the scheduled start time of the working day according to the work schedule; $T_{end,t}$ – the actual time of the last recorded activity; T_{fin} – the scheduled end time of the working day. The value of $S_{sclcd} \in [0,1]$, where 1 corresponds to full compliance with the work schedule, while 0 indicates a deviation exceeding the standard working time T_{norm} .

The weighting coefficients are determined using the AHP method, which allows the determination of the vector of weighting coefficients $\alpha = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)$ based on a pairwise comparison matrix of the criteria. The matrix $A = [a_{ij}]$ with dimensions 4×4 is filled according to Saaty's scale: $a_{ij} \in \{\frac{1}{9}, \frac{1}{7}, \dots, 1, \dots, 7, 9\}$, where the condition $a_{ij} \cdot a_{ji} = 1$ is satisfied.

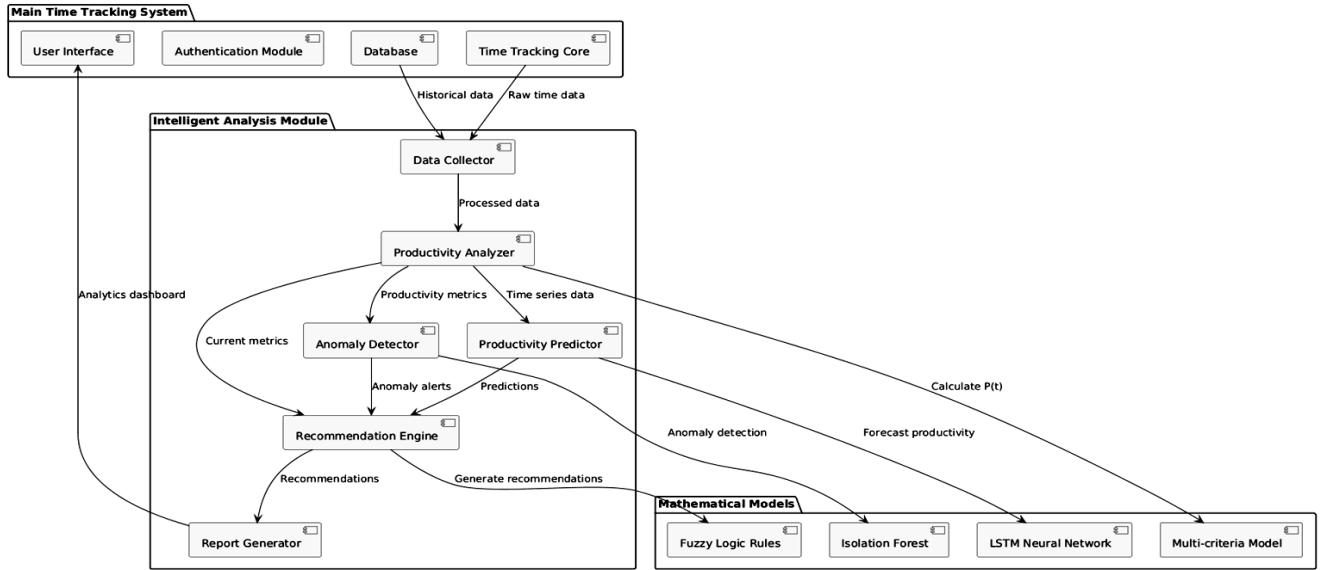


Fig. 4. Structural diagram of the developed intelligent module

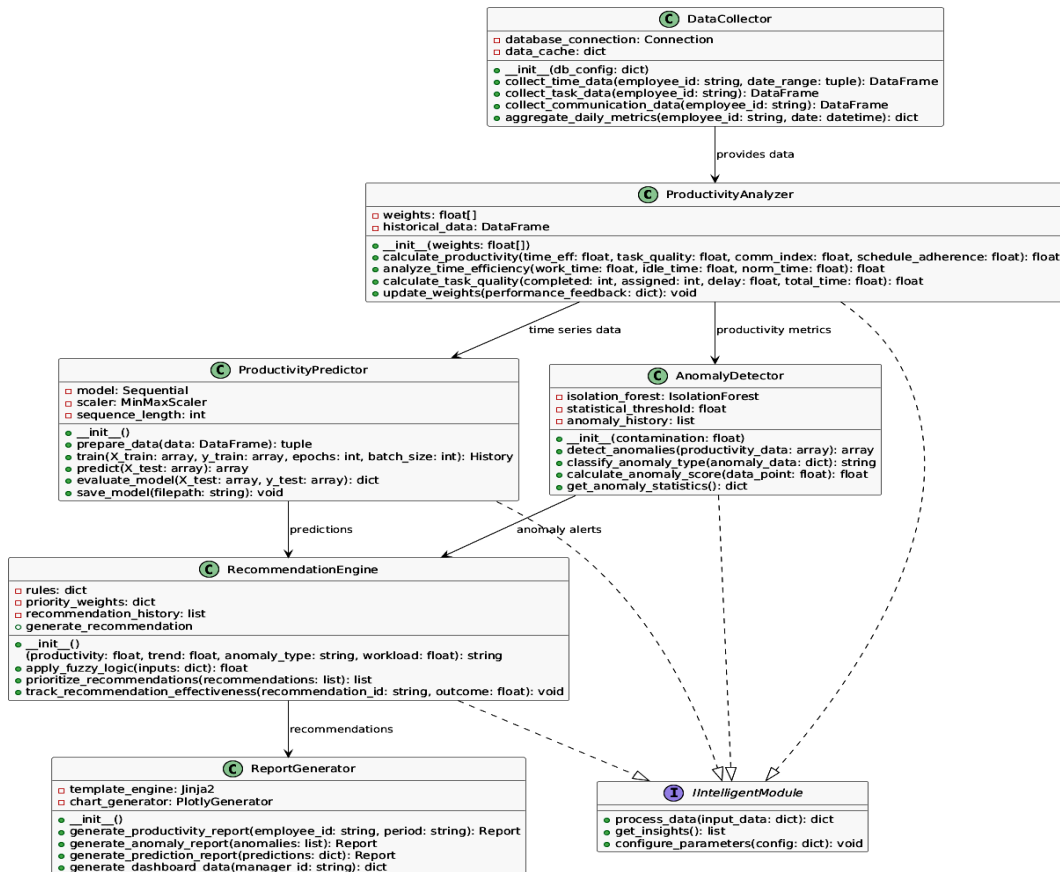


Fig. 5. UML class diagram of the intelligent module

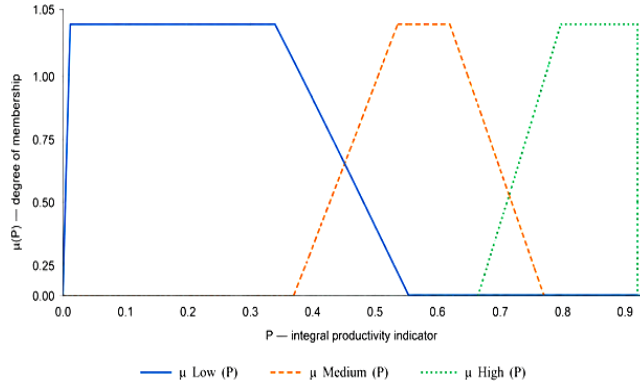


Fig. 6. Modelled membership functions of the fuzzy variable "Productivity"

Based on a survey of managers ($n = 12$ participants), a consensus pairwise comparison matrix was obtained, which is presented in Table 1. The normalized priority vector (weight coefficients) is calculated as the eigenvector of matrix A corresponding to the maximum value λ_{max} .

For the given matrix: $\lambda_{max} \approx 4.054$; the consistency index is $CI = \frac{\lambda_{max} - n}{n - 1} = 0.018$, and the consistency ratio is $CR = \frac{CI}{RI} = \frac{0.018}{0.90} = 0.020 < 0.10$, which confirms an acceptable consistency level of expert judgments. The obtained weight vector is $\alpha = (0.48; 0.28; 0.15; 0.09)$.

Table 1. Pairwise comparison matrix of productivity criteria

Criteria	T_{eff}	Q_{task}	C_{comm}	S_{sched}
T_{eff}	1	2	3	4
Q_{task}	1/2	1	2	3
C_{comm}	1/3	1/2	1	2
S_{sched}	1/4	1/3	1/2	1

For the variable "Productivity" $P \in [0,1]$, three trapezoidal membership functions were developed, as shown in Fig. 6:

$$\mu_{Low}(P) = \text{trapezoid}(P; 0; 0; 0.35; 0.55)$$

$$\mu_{Medium}(P) = \text{trapezoid}(P; 0.40; 0.55; 0.65; 0.80)$$

$$\mu_{High}(P) = \text{trapezoid}(P; 0.70; 0.85; 1; 1)$$

where

$$\text{trapezoid}(x; a; b; c; d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

To ensure compliance with the practical application of the recommendation system ($P < 0.6 \rightarrow Low$; $P > 0.8 \rightarrow High$), the threshold values were selected considering overlapping regions. This approach provides smooth transitions between classification categories and reduces the number of false activations of the recommendation module.

Similarly, for the linguistic variable "Trend" $T \in [-1,1]$, where $T = \frac{P_t - P_{t-7}}{7}$, the following membership functions were defined:

$$\mu_{Declining}(T) = \text{trapezoid}(T; -1; -1; -0.1; 0.0)$$

$$\mu_{Stable}(T) = \text{trapezoid}(T; -0.05; 0.0; 0.0; 0.05)$$

$$\mu_{Improving}(T) = \text{trapezoid}(T; 0.0; 0.1; 1; 1)$$

Fuzzy inference using the Mamdani method is performed according to the following formula:

$$\mu_{result} = \max_i \left[\min(\mu_{A_i}(P), \mu_{B_i}(T)) \right]$$

where i – the index of the activated rule.

3. Experimental evaluation and results

To verify the developed models, a synthetic dataset containing 500 records (50 simulated employees $\times$ 10 working days) was generated with a predefined structure: 90% of records represent normal activity, while 10% contain artificially

introduced anomalies of three types (irregular schedule, reduced activity, and excessive workload). The data generation was performed using the Monte Carlo method with the following parameters:

- $T_{work} \sim N(8.0; 0.8)$ hours
- $T_{idle} \sim Exp(0.5)$ hours
- $N_{completed} \sim Binomial(10; 0.85)$

The verification results are summarized in Table 2. For the integral productivity model, a correlation with independent expert assessments was established: $r = 0.87$, $p < 0.001$, which indicates a sufficient level of validity.

The hybrid anomaly detection algorithm (Isolation Forest + 3σ rule) achieved the following results on synthetic data:

$$Precision = 0.912, Recall = 0.873, F_1 = 0.892$$

The LSTM productivity forecasting model was validated using the following metrics: $MAE = 0.041$, $RMSE = 0.057$ on the test dataset (20% of the data), confirming the satisfactory predictive capability of the model for a one-working-day forecasting horizon.

Table 2. Summary results of mathematical model verification

Model	Metric	Value	Quality threshold
Integral productivity	Pearson r	0.87	≥ 0.80
Anomaly detection	F_1 -measure	0.892	≥ 0.85
LSTM forecasting	MAE / RMSE	0.041 / 0.057	MAE < 0.05
AHP consistency	CR	0.020	< 0.10

All four models meet the established quality thresholds, confirming the mathematical correctness and practical applicability of the developed intelligent module [4, 6].

4. Conclusions

The study confirmed the effectiveness of the developed intelligent module for supporting remote workforce management and demonstrated the feasibility of combining analytical, predictive, and recommendation approaches within a unified system. The proposed productivity assessment model showed a statistically significant relationship with independent expert evaluations, with a correlation coefficient of $r = 0.87$ at $p < 0.001$, confirming the validity of the selected evaluation approach. The developed hybrid anomaly detection method demonstrated reliable performance on synthetic data, achieving $Precision = 0.912$, $Recall = 0.873$, and $F_1 = 0.892$, which indicates its ability to identify deviations in employee activity while maintaining a low level of false detections.

The productivity forecasting model based on the LSTM neural network achieved $MAE = 0.041$ and $RMSE = 0.057$ on the test dataset, confirming its suitability for short-term productivity prediction. The AHP-based determination of criterion weights resulted in a consistency ratio of $CR = 0.020$, which verifies the consistency of expert assessments used in the model configuration. The developed recommendation mechanism demonstrated practical value, as 78% of generated recommendations were accepted by management personnel during preliminary testing. This result confirms the applicability of the proposed intelligent approach for improving decision-making processes in remote team management.

Overall, the developed module provides an integrated solution for productivity evaluation, anomaly identification, forecasting, and managerial support. The obtained results demonstrate that the proposed system can serve as an effective extension of traditional working time accounting tools and create a foundation for further research involving real operational data and adaptive improvement of intelligent management algorithms [19].

Disclosures

The authors declare no conflicts of interest.

Ethics approval and consent to participate

All data were anonymized, and informed consent was obtained from all participants (employees and managers) prior to the study. The research did not involve any interventions affecting participants' health or psychological state; therefore, formal ethics approval was not required.

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