Application of Hybrid Systems SARIMA ANFIS for Monitoring Workforce Dynamics

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Abstract

This paper uses a hybrid SARIMA system and an adaptive neuro-fuzzy inference system (ANFIS) to analyze data on interactions between employees in a real-world entity, including email exchanges, chat messages from meetings, and in-person meetings, for the purpose of detecting position changes such as promotions, demotions, and supervisor changes. The dataset, comprising approximately 184 GB of textual data, includes sixteen features related to employee interactions, such as internal contacts, communication with supervisors, subordinates, and individuals at various levels of the hierarchy. The developed system achieved a detection accuracy of 96%, confirming its usefulness in monitoring personnel processes and optimizing human resource management. In this study, the SARIMA model was combined with the ANFIS system, enabling more precise forecasting of changes over time and the detection of employee behaviors, such as sudden position changes or team interactions. By operating in a quasi-real-time mode, the system allows for the rapid identification of potential irregularities, enhancing organizational security, and supporting personnel decision-making in dynamically changing conditions. The results of our research indicate that hybrid models that integrate the analysis of large datasets and flexible inference systems can effectively support management and behavioral profiling in organizations.

Keywords: Fuzzy rules, ANFIS, ARIMA, Hybrid ARIMA-ANFIS, Workforce Dynamics, Job Role Tracking, Intelligent Systems in HR.

1. Introduction

The structure of modern organizations, especially in dynamic work environments, demands advanced human resource management methods that enable rapid and effective responses to personnel changes. Positional changes, such as promotions, rotations, or resignations, can disrupt team relations and lower productivity. Early identification of such changes is crucial to minimize the risk of downtime and project delays. In the context of rapid organizational growth and increasing volumes of communication data (emails, meetings, chats), traditional HR tools are becoming insufficient. Manual analysis of interactions is time-consuming and prone to error; therefore, automated systems leveraging advanced models, such as hybrid neuro-fuzzy approaches, are playing an increasingly important role. These models enable not only the monitoring of current changes but also forecasting future transformations in the employment structure, supporting resource planning, and team stability. Artificial intelligence techniques are successfully applied in human resource management at various stages of the employee lifecycle. During recruitment, AI is already used for automatic analysis of candidate databases, posting job offers on multiple platforms, and preliminary CV screening, which accelerates and improves the recruitment process while reducing human error, allowing HR departments to focus on strategic talent management [7], [11], [12]. Chatbots are also used in recruitment processes to conduct interviews, ask questions, and administer qualification tests [1], [13]. This allows organizations to quickly identify the most suitable candidates, reducing recruitment time and costs while improving the quality of hires. AI can also support organizational culture by analyzing team interactions, for example, identifying inter-departmental conflicts or lack of cooperation. Based on this information, organizations can implement corrective actions that foster a positive atmosphere and improve internal team relations [9], [14]. Moreover, analysis of performance and training data enables identification of skill gaps and recommendation of personalized professional development paths [10]. Modern HR departments and managers, overwhelmed by responsibilities and organizational changes, often fail to recognize warning signs such as declining engagement or the risk of key employee departures in a timely manner. Delayed responses result in decreased efficiency, project delays, and increased operational costs. To address these challenges, a hybrid SARIMA-ANFIS model is proposed, combining the capabilities of the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model [6], which handles time series analysis, with the Adaptive Neuro-Fuzzy Inference System (ANFIS) [2], which enables forecasting based on historical patterns. This model allows for precise monitoring of team interactions, identifying disruptions in information flow, and predicting events such as positional changes or employee turnover. As a result, managers can take preventive actions to reduce the risk of downtime and improve the stability of the team. The approach presented in this article addresses modern HR management challenges, providing effective support in overseeing and optimizing workforce processes. Based on this, the main research question is formulated: *Does the analysis of communication data using the hybrid SARIMA-ANFIS model enable effective detection and forecasting of positional changes within organizations?* To verify this, the following research hypothesis is proposed: *The SARIMA-ANFIS model, which analyzes employee communication data, enables the identification of three main types of personnel changes (promotions, demotions and supervisor transitions) based on patterns of activity and interaction within the organization.* This hypothesis is verified through the analysis of real-world data collected from companies of varying sizes and through the evaluation of the classification effectiveness of the proposed solution.

2. Materials

The starting point for conducting research on the detection of changes in employment structure was the use of a comprehensive data set concerning employee activity in various organizations. The dataset included information on 2,116 employees from 48 companies operating primarily in office-related sectors such as IT, accounting, administration, wholesale and retail services, and tourism. Each company analyzed employed between 4 and 61 employees (excluding top-level management). Data were collected from May 2018 to August 2024; however, due to disruptions caused by the COVID-19 pandemic, reliable and comparable simulations could only be conducted from April 2022 onward. The data mainly came from Polish companies, with 14 companies based in other European countries, including the Czech Republic, Germany, Lithuania, Slovakia, Italy and Spain. For further analysis, only companies with data for at least 10 employees were selected. This choice was based on consultations with business partners, who indicated that in smaller organizations, where employee integration tends to be stronger, it is more difficult to clearly detect sudden personnel changes. In larger teams, organizational changes are statistically more visible and tend to have more pronounced structural effects, increasing the predictive value of the model. The dataset was used to monitor and classify events related to changes in job positions. A key analytical component was a dynamic graph of the organizational hierarchy, in which each position change was classified based on the relationship between the previous and new supervisor. The data included three main categories of personnel events: *promotion*, *demotion*, and *supervisor_change*. The category *promotion* refers to a shift to a higher level in the organizational hierarchy, *demotion* to a lower level, and *supervisor_change* denoted a change of supervisor without a change in hierarchical level, for example due to team rotation. The classification was based on the relative rank and the path length in the graph between the previous and the new supervisor. Additionally, the analyzed data included detailed descriptions of employees' daily activity, collected from corporate communication systems and calendars. Among the features considered were the number of incoming and outgoing chat messages (`ChatsIn`, `ChatsOut`), emails (`MailsIn`, `MailsOut`), number of meetings (`Meetings`), and interactions with different groups: supervisors (`Supervisor`), direct reports (`DirectReport`), team members (`IntraTeam`), employees from other teams (`CrossTeam`), and external contacts (`External`). The analysis also incorporated the hierarchical structure of interaction participants, for example, contacts with individuals three levels lower (`Rank_3_Lower`), one level higher (`Rank_1_Higher`), or at the same level (`RankSame`). The variable `RankNone` captured the absence of data regarding the participant's position. This data structure enabled a comprehensive analysis of information flow and interaction structures, which are key to understanding and predicting positional changes within organizations. The analysis of this dataset provided a robust foundation for developing models to support human resource management using artificial intelligence methods. The analyses carried out focused on detecting patterns of

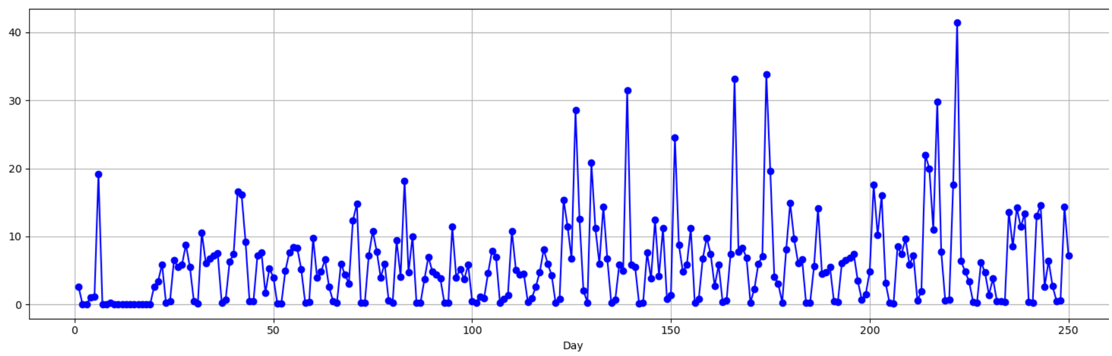

Fig. 1. The number of emails received daily by a user.

cyclic activity and identifying anomalies that could indicate changes in the structure of personnel. Figure 1 shows the number of emails sent on consecutive days. Significant fluctuations are visible, which may reflect cycles of intense communication, for example, related to projects, reorganization, or team activities. Such an analysis enables not only the detection of consistent patterns but also the identification of potential issues that may negatively affect the functioning of the organization. Detected anomalies can signal the need for corrective actions, such as improvements in information flow or team structure. The presented charts serve as examples of tools that support human resource management and the optimization of organizational processes.

The data used in this research were obtained from corporate communication and organizational systems. In Microsoft 365-based environments, data were collected from Exchange Online (Outlook), Microsoft Teams, and Outlook Calendar, while organizational structure information was retrieved from Azure Active Directory using the Microsoft Graph API. For companies using a Linux-based infrastructure, data sources included `Postfix` and `Dovecot` mail servers, chat systems such as `Rocket.Chat` and `Mattermost`, and calendars based on `Nextcloud Calendar` or `Radicale`. The organizational structure data was reconstructed from sources such as `OpenLDAP` or internal HR systems. In all cases, only metadata was analyzed, without access to the message content or the private information of the participants. Data were obtained with the consent of the participating entities and processed in accordance with applicable data protection regulations (including GDPR). The employment dynamics anal-

Table 1. Dataset characteristics

Attribute	Value / Range
Number of companies	46
Countries of origin	Poland (31), Germany (4), Czech Republic (2), Lithuania (2), Slovakia (1), Italy (2), Spain (3)
Industries	IT, administration, accounting, wholesale sales, tourism
Company size range	4–61 employees (excluding top management)
Total number of employees	2,116
Data collection period	May 2018 – August 2024
Analysis period	April 2022 – August 2024
Minimum company size	more than 10 employees
Event categories	*promotion*, *demotion*, *supervisor_change*
Activity types	Email, chat, meetings, intra-team and cross-team interactions
Data sources	Microsoft 365 (Exchange, Teams, Graph API), Postfix, Rocket.Chat, OpenLDAP, Nextcloud, Radicale

ysis system based on the hybrid SARIMA-ANFIS model was implemented in Python using the NumPy, PyTorch, scikit-learn, and Matplotlib libraries. The employee activity data (184 GB) were stored in Microsoft SQL Server and binary files, with the database integration written in C#. The test environment included a server with an Intel i7-12700KF processor, 128 GB RAM, and RAID 0/1 arrays, ensuring efficient analysis and repeatable data processing.

3. Methods and the Hybrid SARIMA-ANFIS Model

To forecast changes in the employment structure and identify patterns of activity of employees, a hybrid SARIMA-ANFIS model was developed. The SARIMA model [3], an extension of the classical ARIMA model [6], enables modeling of seasonality and cyclicality in time-series data. This is particularly important in analyzing team turnover, periodic spikes in activity, or communication drops during vacation periods. The structure of the SARIMA model is denoted as SARIMA$(p, d, q)(P, D, Q)_m$, where (p, d, q) and (P, D, Q) represent the nonseasonal and seasonal components, respectively, and m indicates the length of the seasonal cycle (e.g., $m = 7$ for weekly data). Mathematically, the model is represented as

$$\Phi(B^m)\varphi(B)(1 - B)^d(1 - B^m)^D x_t = \Theta(B^m)\theta(B)\varepsilon_t \tag{1}$$

where B is the backshift operator, φ and Φ are autoregressive polynomials, θ and Θ are moving average polynomials, and ε_t is the error term. Although the SARIMA model allows for the identification of repetitive behavioral patterns, it lacks the capacity to adaptively detect atypical events. Therefore, it was extended with an ANFIS (Adaptive Neuro-Fuzzy Inference System) component [4], which enables modeling of nonlinear relationships and dynamic adaptation to changing organizational conditions. The proposed SARIMA-ANFIS system (Fig. 2) integrates time series forecasts (e.g., number of emails, meetings) with behavioral features of employees (e.g., interactions with supervisors, subordinates, external contacts), allowing for the detection

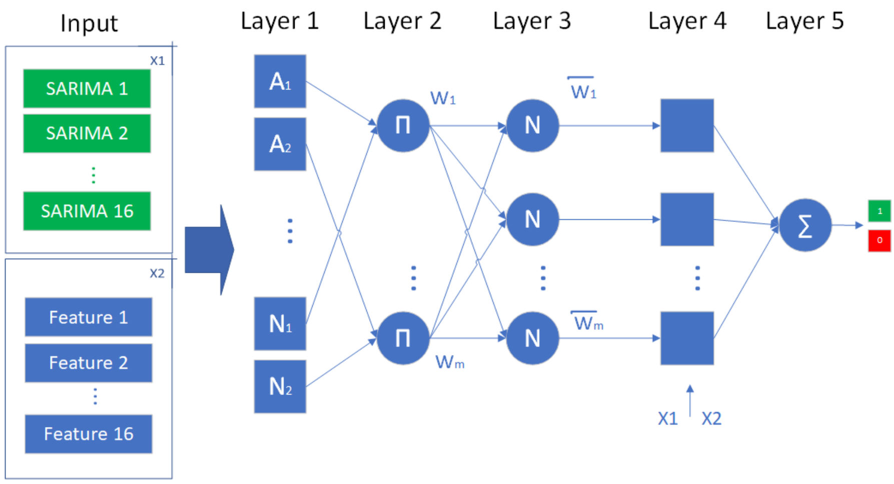

Fig. 2. Integration of the ANFIS system with the SARIMA model enables the detection of an anomaly.

of both cyclic patterns and anomalies, such as sudden reorganizations or promotions preceded by increased activity. The combination of an interpretable statistical model with the flexibility of a fuzzy system makes the solution an effective decision support tool in human resource management. To classify positional changes, three detectors were developed corresponding to the three types of personnel events: *promotion*, *demotion*, and *supervisor change*. Each detector integrates seasonal model forecasts (SARIMA) with behavioral characteristics such as interactions with supervisors, team members, or external parties. This enables the identification of both cyclic activity patterns and deviations from the norm that may signal reorganizations or personnel changes. The input data includes, among others, the number of emails, meetings, interaction patterns, and seasonal forecasts. The system transforms these into a form that enables the detection of one of the three types of changes. Promotion is typically associated with increased interaction with higher-level individuals and greater participation in strategic tasks. Demotions are detected through opposite signals, while supervisor changes are identified by transformations in the employee's communication network. The analysis employed the ANFIS model, based on the Takagi–Sugeno–Kang (TSK) structure, which combines mechanisms of fuzzy systems and neural networks. The decision rules in the TSK model take the form of deterministic functions, with parameters tuned during the training process. This enables the system to dynamically model nonlinear relationships in organizational data, adapting to changing patterns, and supporting the prediction of HR processes. In the first layer, different membership functions were applied, adapted to the nature of the input data. For variables representing seasonal activity patterns, a sigmoid function was used: $\mu(x) = 1/(1 + e^{-a(x-c)})$, where the parameter a controls the steepness of the curve and c sets the threshold value. This allows for the analysis of gradual activity changes resulting from long-term trends. For behavioral features such as the number of emails, meetings, or interactions with supervisors, a trapezoidal function was used

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & b < x \leq c \\ \frac{d-x}{d-c}, & c < x \leq d \\ 0, & x > d \end{cases} \tag{2}$$

In the second layer, fuzzy logical AND is performed. The input membership values are combined as follows $w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y)$. The third layer performs normalization of rule weights

Table 2. Classification results for models detecting positional changes

Type of Change	Accuracy	Precision	Recall	F1-score
Promotion	96.1%	94.8%	97.3%	96.0%
Demotion	95.5%	93.9%	96.7%	95.2%
Supervisor change	96.4%	95.2%	97.1%	96.1%

$\tilde{w}_i = w_i / \sum_{j=1}^{m} w_j$. In the fourth layer, the rule outputs are calculated using linear functions $f_i = p_i \cdot x + q_i \cdot y + r_i$, where the parameters p_i, q_i, r_i are adjusted during the training process. The final system output (fifth layer) is the weighted average of the rule outputs $f = \sum_{i=1}^{m} \tilde{w}_i \cdot f_i$. The ANFIS model, based on the adaptive neuro-fuzzy inference system, integrates SARIMA data by accounting for seasonality, temporal dependencies, and nonlinear interactions. This hybrid approach enables more accurate forecasting of time-based processes, such as changes in organizational communication. The model is trained by adjusting the parameters of the membership function and inference rules using the backpropagation error method [4]. The ANFIS structure, consisting of five layers, allows data to be processed from fuzzification to defuzzification, enhancing predictive accuracy.

4. Results

In the ANFIS model, the activation function was replaced with a modified Gaussian-based membership function, which allows for a better representation of gradual changes in the analyzed data. It is described by the equation

$$\mu(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \tag{3}$$

where c denotes the center of the function and σ controls the width of the interval in which input values are considered the most probable. This modification enabled smoother integration with forecasts generated by SARIMA. Using the Gaussian function instead of the classical activation function allowed for a more natural modeling of uncertainty and a more accurate reflection of continuous changes in workforce dynamics, which is crucial for analyzing organizational communication processes. To classify positional changes within the organization, three independent learning models were developed, each tailored to detect one of the three classes: *promotion*, *demotion*, and *supervisor change*. A one-vs-all training approach [8], in which for each model, all data not related to the target class were labeled as 0 (no change), while examples belonging to the target class were labeled as 1 (positive classification). This allowed each system to be trained specifically for the accurate detection of a given type of change while utilizing the full dataset. Classification performance was evaluated using standard metrics such as accuracy, precision, recall, and the F1-score. Furthermore, the mean squared error (MSE) [5] and the binary classification error (indicating the proportion of incorrect predictions among all test samples) were used to assess model error. The system was tested on a real-world dataset covering 2,116 employees, allowing validation of its ability to detect positional changes. Final classification results for each of the three models are presented in Table 2. The test results indicate high classification performance, with an average detection accuracy of 96%. The best performance was observed for the supervisor change classification (96.4%), which confirms the distinctiveness of such events in the communication data. The model effectively recognizes real personnel changes, making it a solid foundation for further development, particularly toward forecasting future changes in employment structure. Figure 3 presents the membership functions used in the SARIMA-ANFIS model. The upper part of the plots shows Gaussian functions (blue) representing seasonal communication patterns, e.g. increased message volume during specific times of day or months. The lower part shows trapezoidal functions (orange), used to assess behav-

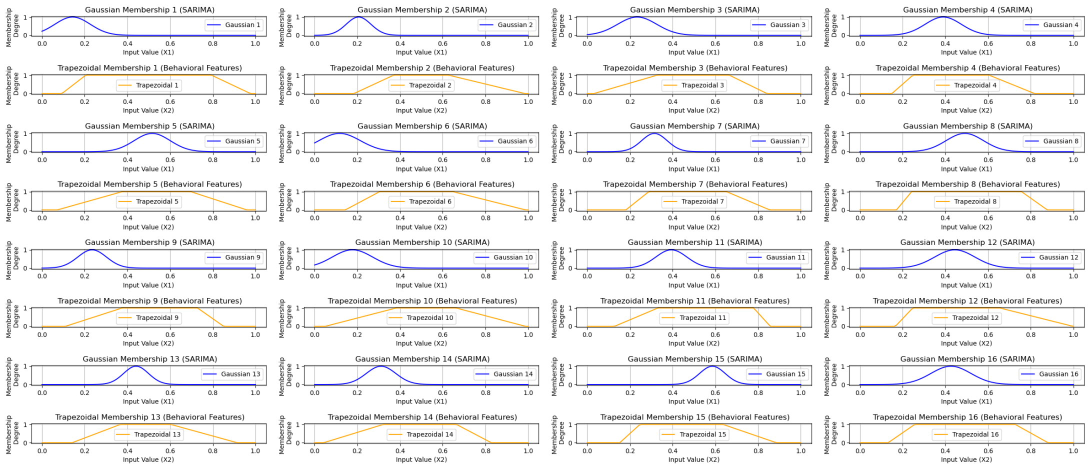

Fig. 3. Membership functions used in the SARIMA-ANFIS model.

Table 3. Validation results of the SARIMA-ANFIS model on an independent test set (100 users)

Type of Change	Number of Cases	Correctly Detected	Accuracy
No change	71	58	81.7%
Promotion	11	7	63.6%
Demotion	6	5	83.3%
Supervisor change	12	5	41.7%

ioral features such as the number of interactions or meetings. The combination of both types of functions allows the model to identify regular trends and sudden changes in activity, enhancing its ability to detect anomalies and better support organizational structure management.

5. Conclusions

The presented hybrid *SARIMA-ANFIS* system enables effective monitoring of promotions, demotions, and supervisor changes based on communication data. The integration of the seasonal SARIMA model with the adaptive ANFIS system allowed for high classification accuracy, automating the analysis of employment dynamics and supporting HR decision-making. As part of the validation process, the model's effectiveness was confirmed on an independent dataset involving 100 employees not included in the training or earlier evaluation phase. These results demonstrate the model's good generalization capabilities and practical applicability in real-world conditions, while also highlighting the need for further optimization in detecting structural changes not directly related to promotion or demotion. Future work includes extending the system with additional predictive modules and integrating new data sources, such as performance evaluations and project-related information, which will further enhance the system's ability to anticipate changes in organizational structure.

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