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Palonyi A.S.
Ukrainian State Flight Academy

Nechypurenko A.G.
Ukrainian State Flight Academy

HYBRID DECISION SUPPORT SYSTEM FOR ADAPTIVE ASSESSMENT AND MANAGEMENT OF AIR TRAFFIC CONTROLLERS' OCCUPATIONAL STRESS IN REAL-TIME

The subject matter of the article is the occupational stress of air traffic controllers (ATCOs), methodological approaches to its multilevel assessment, and management mechanisms in the dynamic air traffic control (ATC) environment. The research focuses on developing an integrated system that combines the Best-Worst Method (BWM) for determining stressor weights, a multilevel fuzzy inference system (FIS) for stress level assessment, and a dynamic parameter adaptation module operating in real-time. The goal of the article is to construct a hybrid decision support system (DSS) for continuous assessment of ATCOs' operational stress with generation of personalized intervention recommendations, accounting for the dynamic nature of stressors, individual ATCO characteristics, and contextual factors of the work environment. The tasks of the article include: systematization and classification of ATCOs' professional stressors by their sources; development of a methodology for dynamic adaptation of stressor weights considering shift phase, traffic level, and individual ATCO profile; construction of a three-level hierarchical fuzzy inference system for aggregating stressor impacts through five aggregator components; formalization of the mechanism for generating optimal stress management recommendations based on predicting future system states. Research methods include: Best-Worst Method (BWM) for determining baseline stressor weights, fuzzy logic for modeling uncertainty in stress assessment, gradient descent for system parameter adaptation, and systems analysis for identifying relationships between components. The obtained results include: a functional DSS model represented as a tuple of components with formalized relationships; a proposed three-factor model for dynamic stressor weight adaptation; a developed cyclic system operation algorithm with a 60-second update interval; a defined database structure for storing system state history. The scientific novelty lies in integrating the BWM method with dynamic adaptation mechanisms to account for real-time contextual changes, developing a three-level FIS to avoid combinatorial rule explosion while maintaining assessment accuracy, and formalizing a self-learning module based on gradient descent for automatic system parameter adjustment according to accumulated experience. The practical significance of the developed system lies in its applicability for operational monitoring of ATCOs' conditions, predicting critical situations, and forming justified management decisions regarding workload distribution and shift organization.

Key words: *air traffic controller, occupational stress, decision support system, fuzzy logic, dynamic adaptation, real-time monitoring.*

Formulation of the problem. The growth of air traffic intensity, increasing complexity of airspace, and rising flight safety requirements create preconditions for the accumulation of professional stress, which may lead to decreased performance efficiency, erroneous actions, and incidents. Professional stress and fatigue of air traffic controllers (ATCOs) are constant risk factors for flight safety when high cognitive demands of controller work, irregular shifts, and time pressure are combined. A recent multicenter study funded by EASA and conducted on a sample of six European air navigation service providers showed that 5.6% of shifts are associated with critical levels of fatigue. The leading determinants were recognized as night shifts, complex weather conditions, monotonous traffic situations, accumulated "sleep debt," and prolonged work without breaks [1]. The increase in critical fatigue risk is statistically associated with the type of shift: night shifts critically increase risk, morning shifts have significantly elevated risks compared to day shifts, while evening shifts have relatively lower fatigue levels (probable manifestation of the wake maintenance zone effect). Professional environment factors (monotonous traffic, complex weather conditions and tasks (e.g., need for coordination with colleagues) significantly increase the risk of critical fatigue. An additional day of rest after a night shift reduces the indicated risk by ~43%, while a 10% increase in "sleep debt" increases the risk by ~86% [1].

Chronic professional stress leads to emotional exhaustion and professional burnout. A large survey of 457 Chinese ATCOs showed that 83.59% of respondents have signs of professional burnout. Higher levels of effort-reward imbalance (ERI) were associated with more severe burnout, while social support acted as a protective factor [2]. These findings are consistent with contemporary cross-industry models: perceived stress positively correlates with the composite burnout index in the link burnout questionnaire (LBQ), while self-efficacy correlates negatively [3].

In civil aviation, the Fatigue Risk Management System (FRMS) approach dominates, which is defined in International Civil Aviation Organization (ICAO) documents as "a data-driven means of continuously monitoring and managing fatigue-related safety risks, based upon scientific principles, knowledge and operational experience" [4]. The EU regulatory context contains mandatory elements for fatigue and stress prevention, particularly EU 2015/340 regarding ATCO training and EU 2017/373 for shift and rest organization. Recent field studies in the EU, funded by EASA, rely on these standards, combining schedule analysis, FRMS practices, and field data collection at air navigation service providers (ANSP) [5, 6]. However, existing fatigue/stress management procedures in the controller environment do not provide sufficiently refined, personalized, and responsive correction of workload, breaks, and task distribution in response to ATCO psychophysiological state dynamics. This creates a need for decision support systems (DSS) that integrate subjective questionnaires, physiological/behavioral indicators, shift context, and tactical-operational events for adaptive management of ATCO stress during shifts.

Analysis of recent research and publications. Review-empirical works confirm the systemic contribution of workload, temporal regimes, and work environment (lighting, noise, ergonomics) to increased stress and deteriorated ATCO performance. Analytical research in the sphere of job demands-resources (JD-R) and effort-reward imbalance (ERI) explains how high cognitive complexity, time pressure, monotony, and limited control cause acute fatigue and, upon transition to a chronic state, burnout [3]. In a sample among military ATCOs, it has been shown that decision overload, intensive or "inconvenient" shifts, and unfavorable workplace conditions are associated with loss of "situational picture" and decreased control quality [7, 8].

In studies of ATCO stress and fatigue levels, validated questionnaires are systematically applied: the Perceived Stress Scale (PSS-10), General Self-Efficacy Scale (GSES), Link Burnout Questionnaire (LBQ) with subscales of psychophysical exhaustion, relationship deterioration, professional ineffectiveness, disappointment, the Job Content Questionnaire (JCQ) for psychological job assessment, and the effort-reward imbalance model (ERI). Additionally, the MBI-GS (Maslach Burnout Inventory-General Survey) questionnaire is used to identify burnout, capturing emotional exhaustion, cynicism, and professional efficacy [2, 3]. Protocols combining questionnaires with objective indicators (sleep actigraphy, behavioral tests) are increasingly applied in projects developing reliable FRMS.

Field and near-realistic conditions studies have shown the informativeness of such fatigue assessment metrics in ATCO as the percentage of eyelid closure time (PERCLOS) [9]. Heart rate variability (HRV) demonstrates sensitivity to mental workload changes during air traffic control task simulation. The relevance of temporal and spectral HRV indicators has been confirmed, as well as the importance of time scales for biomarker interpretation [10]. For rapid detection of cognitive load, EEG studies emphasize the diagnostic value of indicators in ranges that include γ-waves and the applicability of algorithms from classical (mRMR feature selection) to deep convolutional neural networks (CNNs) models [11, 12]. A separate direction should be identified as non-invasive eye tracking and other biobehavioral predictors of ATCO workload using machine learning (ML) models [13]. While the aforementioned methods are actively developing, questions of external validity and operational acceptability remain open.

The analysis of practical measures has identified a typical triad of strategies: primary (ATCO shift design/rostering, workplace ergonomics), secondary (professional training, coping techniques), tertiary (rehabilitation and support), however, most interventions remain planned or reactive and are not oriented toward personalized proactive real-time solutions [8]. EU regulatory requirements coordinate the presence of procedures and training modules on fatigue and stress, and EASA thematic reports (2024) state a high level of process formalization (100% of ANSPs have procedures), but rather limited regular data collection regarding sleep/fatigue (~40% – quarterly or annually) [5, 11]. Overall, the modern industry is ready for the implementation of hybrid DSS with multimodal data (questionnaires, sensors, task context) and algorithmic decision support.

Task statement. The main objective of the article is to develop and formalize a hybrid decision support system for adaptive assessment of air traffic controllers' professional stress in real-time with the capability of generating personalized recommendations for management interventions.

Outline of the main material of the study. Our current research is based on: the functional model of ATCO stress management (the "white box model") and the functional requirements for DSS of automated occupational stress management system [14]; classification system of key occupational stressors and system dynamics model of ATCOs' job stress components [15].

Considering the multifaceted nature of the ATCOs' professional stress management problem, the complexity of interrelationships between heterogeneous stressors, and the necessity for adaptive system behavior in real-time [14], it is proposed to represent the DSS as a structured mathematical model. Such formalization will allow for clear definition of the system's functional modules, their interaction, and information processing mechanisms at each stage of decision-making.

Based on our previous research [15], stressors are classified into six clusters, presented in Fig. 1.

The functional model of DSS is described by the tuple:

$$DSS_{ATCO} = \langle S, W, F, A, D, R \rangle \tag{1}$$

where: S – set of stressors (high air traffic intensity, technical failures, complex weather conditions, etc.): $S=\{s_1,\ldots,s_n\}$; W – dynamic stressor weights; F – fuzzy inference system; A – adaptation/self-learning module; D – database of system and ATCO' state; R – stress management recommendation mechanism.

According to system dynamics model of ATCOs' job stress components [15] the level of perceived overall occupational stress is determined by five component-aggregators of the model, which accumulate the impact of job stressors of various sources, the cumulative effect of which can be quantitatively measured – "level of perceived personal control over the work situations" (PC), "level of perceived the teamwork quality" (TW), "level of perceived job demands" (JD), "level of perceived background stress" (BS), and "level of perceived stress manageability" (SM).

Let us briefly consider the DSS operating principle (Fig. 2). Within a defined time interval (Δt), the DSS captures indicators from various sources: physiology (HR, RR, EDA), air traffic parameters,

Fig. 1. Occupational stressor clusters of ATCO

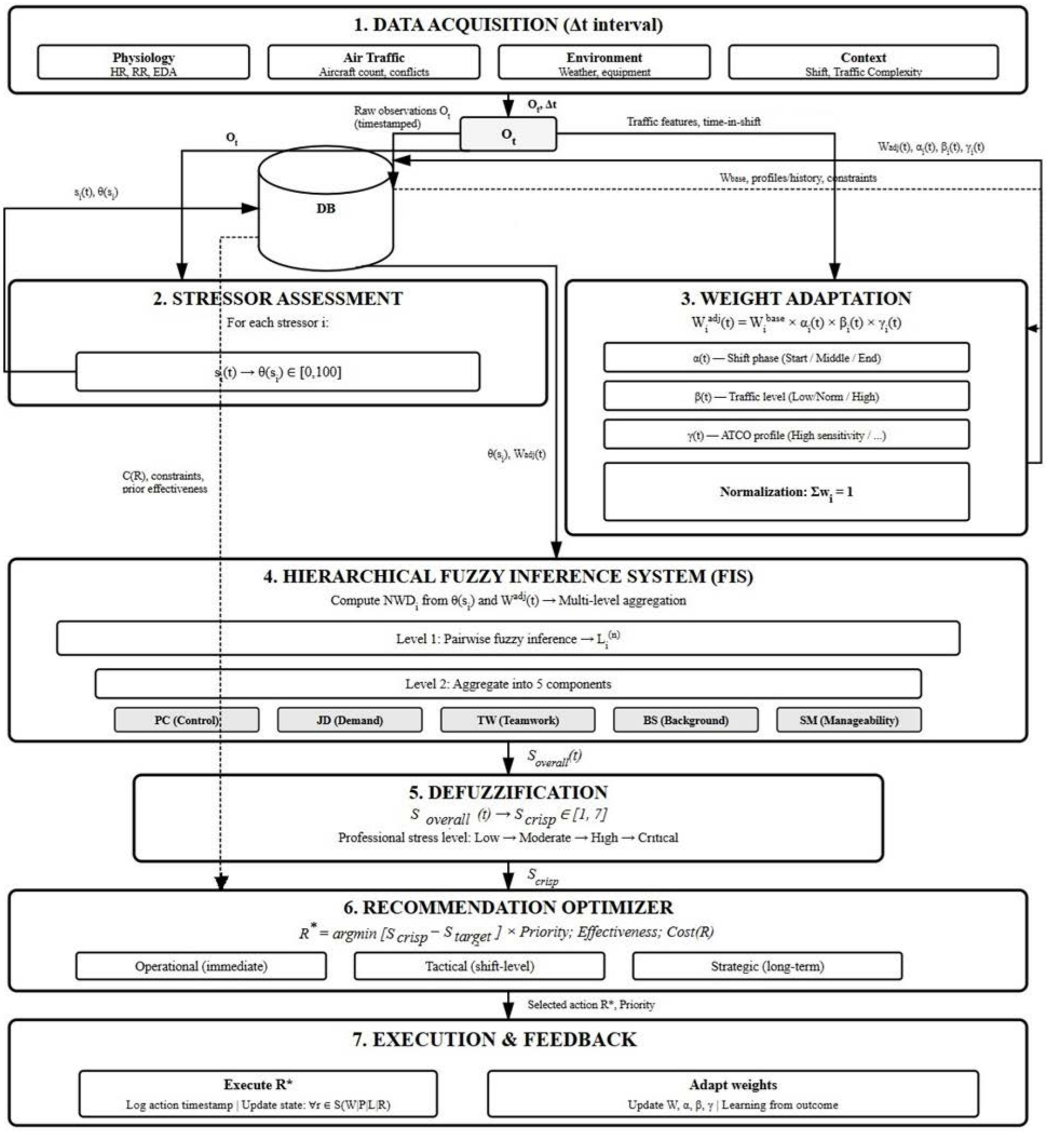

Fig. 2. Functional model of DSS

weather conditions, ATCO equipment status. This "snapshot" of the state forms the observation vector O_t. It is recorded in the database (DB) and sent for further processing. Next, stressor assessment occurs. For each stressor, the system obtains an instantaneous value $s_i(t)$, transforms it into a comparable score $\theta(s_i)$ on a 0-100 scale, and calculates the relative, mutually comparable contribution – normalized weighted (stress) driver (NWD_i). This allows us to understand not only "how much" each factor manifested, but also "how important" it is in the current context. To ensure this importance corresponds to the actual situation, weight adaptation is triggered. Base weights are recalculated into vector W(t) considering three modifiers that will be discussed later. After updating, weights are normalized, and the result is stored in DB – this makes the system's behavior context-sensitive but controlled. Updated contributions NWD and weights W(t) are fed into the multilevel FIS. After defuzzification, scalar $S_{crisp} \in [1,7]$ is determined (scale from "low" to "critical"). At the top of the hierarchy, the integral indicator $S_{overall}$ (t) is formed. To transition from "fuzzy" description to a specific value of overall stress level, the system performs defuzzification: from $S_{overall}$ (t), S_crisp is determined on the scale [1...7] – professional stress level: from low to critical. Based on the determined professional stress level of the ATCO, the recommendation optimizer selects action R* that best reduces deviation from the desired level (goal) considering priority, expected effectiveness, and cost C(R). As a result of this module's functioning, the supervisor receives clearly formulated intervention options: operational (immediately), tactical (for the duration of the controller shift), or strategic

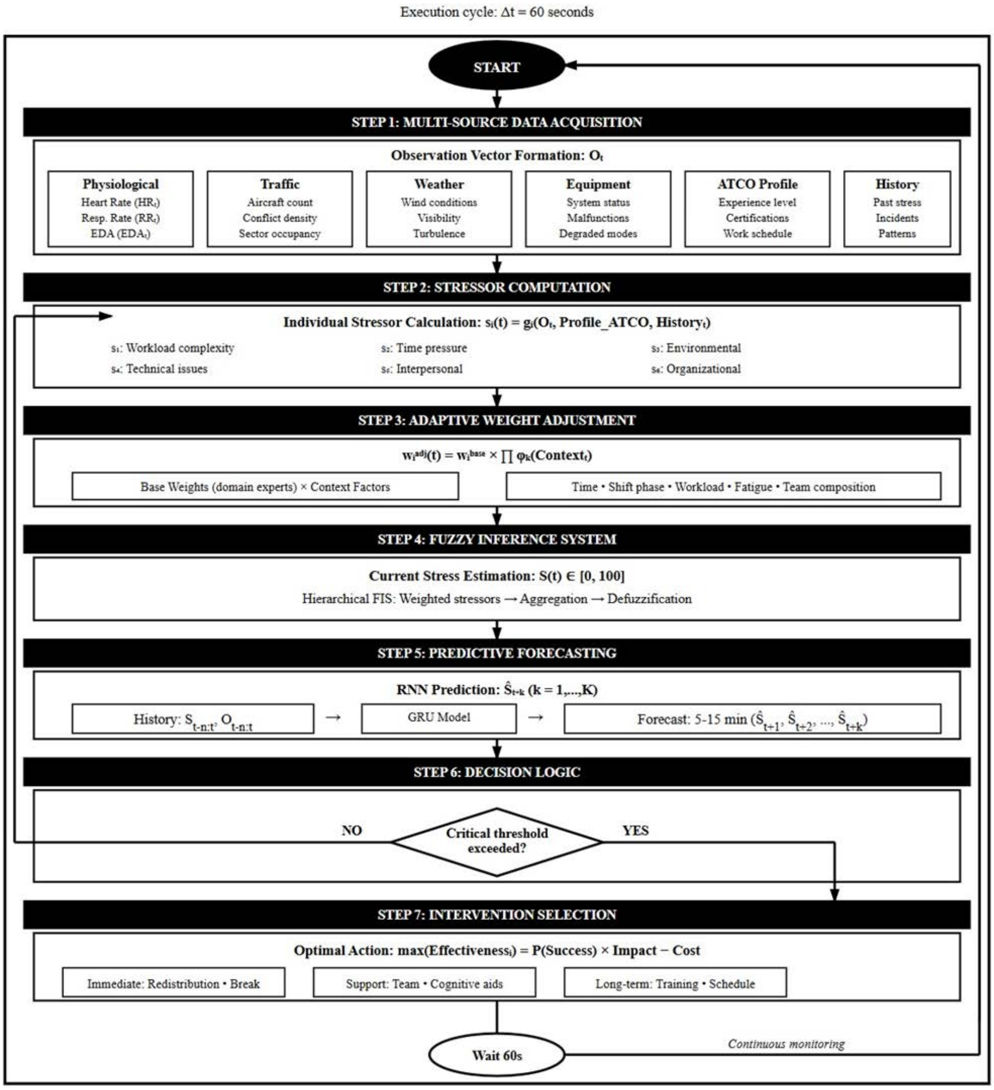

Fig. 3. Real-time monitoring and intervention algorithm

(longer-term perspective). Finally, the Execution & Feedback block performs the selected action, records what exactly was done, updates the state vector Ψ_t (S, W, P, H, R) in DB, and most importantly, returns the impact back into the cycle: weights and modifiers are adjusted considering the result. After Δt seconds, a new cycle begins – already accounting for the recently acquired experience.

The database of system and ATCOs' state stores history Ψ_t, event logs, parameters, applied recommendations, that is, everything needed for audit and model training, including: S_t – stressor state at time t (particularly, integral fuzzy output) and defuzzified stress level; W_t – weights and their modifiers; P_t – fuzzy inference system parameters for each input variable and linguistic label; H_t – history and hidden states of predictive model (RNN), event counters, time-in-shift, accumulated background stress, etc.; R_t – selected actions; priorities, expected effectiveness and cost.

The cyclical process of DSS functioning in general form is presented in Fig. 3.

The proposed methodology is based on the integration of three key components: the Best-Worst Method (BWM) for determining stressor weights, a Fuzzy Inference System (FIS) for stress level assessment, and a dynamic adaptation module for ensuring system flexibility in real-time. Initial (base) stressor weights (w_j^{base}) are determined using the Best-Worst Method (BWM) by solving the corresponding linear optimization problem for consistent comparison vectors "best to others" and "others to worst" (Fig. 4).

In our work, the traditional BWM is extended with a dynamic stressor weight adaptation module. Initial weights are determined using the standard BWM procedure with subsequent weight adaptation.

To determine a normalized and internally consistent set of base weights (w_j^{base}) for stressors, which serve as the foundation for dynamic weight adaptation, the following optimization problem is solved:

$$
\begin{aligned}
&\min \xi \\
&\text{s.t. } w_B - a_{B_j} \cdot w_j \le \xi \qquad \forall_j = 1,\dots,n \\
&a_{B_j} \cdot w_j - w_B \le \xi \qquad \forall_j = 1,\dots,n \\
&w_j - a_{jW} \cdot w_W \le \xi \qquad \forall_j = 1,\dots,n \\
&a_{jW} \cdot w_W - w_j \le \xi \qquad \forall_j = 1,\dots,n \\
&\textstyle\sum_{\{j=1\}}^{n} w_j = 1,\; w_j \ge 0 \\
&\forall_j = 1,\dots,n
\end{aligned}
\tag{2}
$$

where: n – number of stressors; $j \in \{1,\dots,n\}$ – stressor index; w_j – sought base weights of stressors (normalized importance weights for each stressor *j*); w_B – weight of the best (most important) stressor; w_W – weight of the worst (least important) stressor; a_{Bj} – intensity of preference “best over *j*”; a_{jW} – intensity of preference “*j* over worst”; ξ – maximum deviation variable.

Dynamic weight adaptation to the operational context is performed according to the following formulation:

$$
w_j^{adj(t)} = w_j^{base} \cdot \pm_j(t) \cdot {}^{2}{}_j(t) \cdot {}^{3}{}_j(t) \tag{3}
$$

where: w_j^{base} – base weight obtained by BWM method; $\alpha_j(t)$ – shift phase coefficient (beginning/middle/end); $\beta_j(t)$ – air traffic level coefficient (the higher it is, the more the weights of “sensitive” stressors increase); $\gamma_j(t)$ – individual controller profile coefficient.

Let us examine each of these adaptation parameters in more detail. The shift phase coefficient for air traffic controllers $\alpha_j(t)$:

$$
\begin{aligned}
&\alpha_j(t) = \{1.0 + 0.1 \cdot \sin\left(\frac{\pi t}{T_{shift}}\right)\text{ – for operational stressors;} \\
&1.2_{+0.2\cdot\cos\left(\frac{2\pi t}{T_{shift}}\right)}\text{ – for cognitive stressors;} \\
&1.0 \text{ – for other stressor groups}\}
\end{aligned}
\tag{4}
$$

where: 0.1 and 0.2 are controlled amplitudes that do not “overwhelm” the base BWM weights but provide 10-40% variation throughout the shift and always maintain the coefficient ≥1.0 (without reducing weight below the base level). For example, operational stressors are less dependent on the controller shift phase (more on external events and air traffic complexity, which $\beta_{j(t)}$ accounts for), so seasonality is limited within +10% of base: $\alpha_j(t) \in [1.0, 1.1]$.

The ATCO shift phase $\alpha_{j(t)}$ is not set arbitrarily – its parameters are estimated from data to reflect real workload dynamics throughout the ATCO shift. For each stressor cluster, we estimate $\alpha_j(t)$ using least squares model on $S_{overall}$ residuals after adjusting for $\beta_j(t)$ and $\gamma_j(t)$ effects.

Air traffic level coefficient $\beta_{j(t)}$:

$$
\beta_j(t) = 1 + k_j \cdot \left(\frac{N_{actual}(t) - N_{avg}}{N_{max - N_{avg}}}\right) \tag{5}
$$

where: $N_{actual}(t)$ – sector loading indicator (current air traffic intensity); N_{avg} – average number of aircraft (smoothed average value for the last 30 days referenced to hour of day/day); N_{max} – maximum sector capacity (normative value); k_j – stressor sensitivity coefficient to air traffic.

Individual ATCO differences are accounted for through profile feature vector *z* and historical states. We use an affine exponential form:

$$
\gamma_j(t) = \exp\left(,_{0j} + ,_j^{T} z(t)\right) \tag{6}
$$

where θ – identified through gradient descent using a loss function that minimizes the discrepancy between predicted and observed stress levels. This parameterization preserves the positivity and monotonicity of $\gamma_j(t)$ and integrates with the self-learning module.

The adaptation/self-learning module adjusts weights and membership function parameters through feedback:

$$
\Delta w_j = \eta \cdot \left(S_{target} - S_{actual}\right) \cdot \left(\frac{\partial S_{actual}}{\partial w_j}\right) \tag{7}
$$

where ”w_j – increment (change step) of j-th stressor weight (w_j) at current time step; η – learning rate for weights; S_{target} – target stress level determined by expert judgment; S_{actual} – actually computed stress level at time *t* after defuzzification (S_{crisp} ∈ [1,7]); $\frac{\partial S_{actual}}{\partial w_j}$ – system output sensitivity to weight w_j (derivative; how much the stress assessment will change if the specific stressor weight is slightly changed while other variables remain fixed).

The air traffic controller profile encompasses total tenure as an air traffic controller, experience at the specific working position, chronotype, reaction time, baseline heart rate variability (HRV) values and electrodermal activity (EDA) parameters; subjective workload; team stability; recency of training/breaks. The profile is stored in the database along with event logs, state history, and FIS parameters, enabling personalized adaptation $\gamma_j(t)$ and membership function adjustments.

To avoid combinatorial rule explosion, a three-level hierarchical FIS is applied. At Level 1, intermediate assessments of relevant stressor pair interactions ($L_{ij}^{(1)}(t)$) are computed. At Level 2, stress level aggregates PC, JD, TW, BS, SM are formed as defuzzified outputs of corresponding FIS_2 subsystems that integrate selected $L_{ij}^{(1)}(t)$. At Level 3, we obtain fuzzy integral assessment $S_{overall}(t) = FIS_3(PC, JD, TW, BS, SM)$ and defuzzify it using center of gravity method, obtaining scalar $S_{crisp(t)} \in [1,7]$. Decrease in $PC(t) < PC_{ref}$ increases $\gamma_{j(t)}$ for cognitive stressors, raising their adjusted weights $w_j^{adj}(t)$, shifting FIS inference

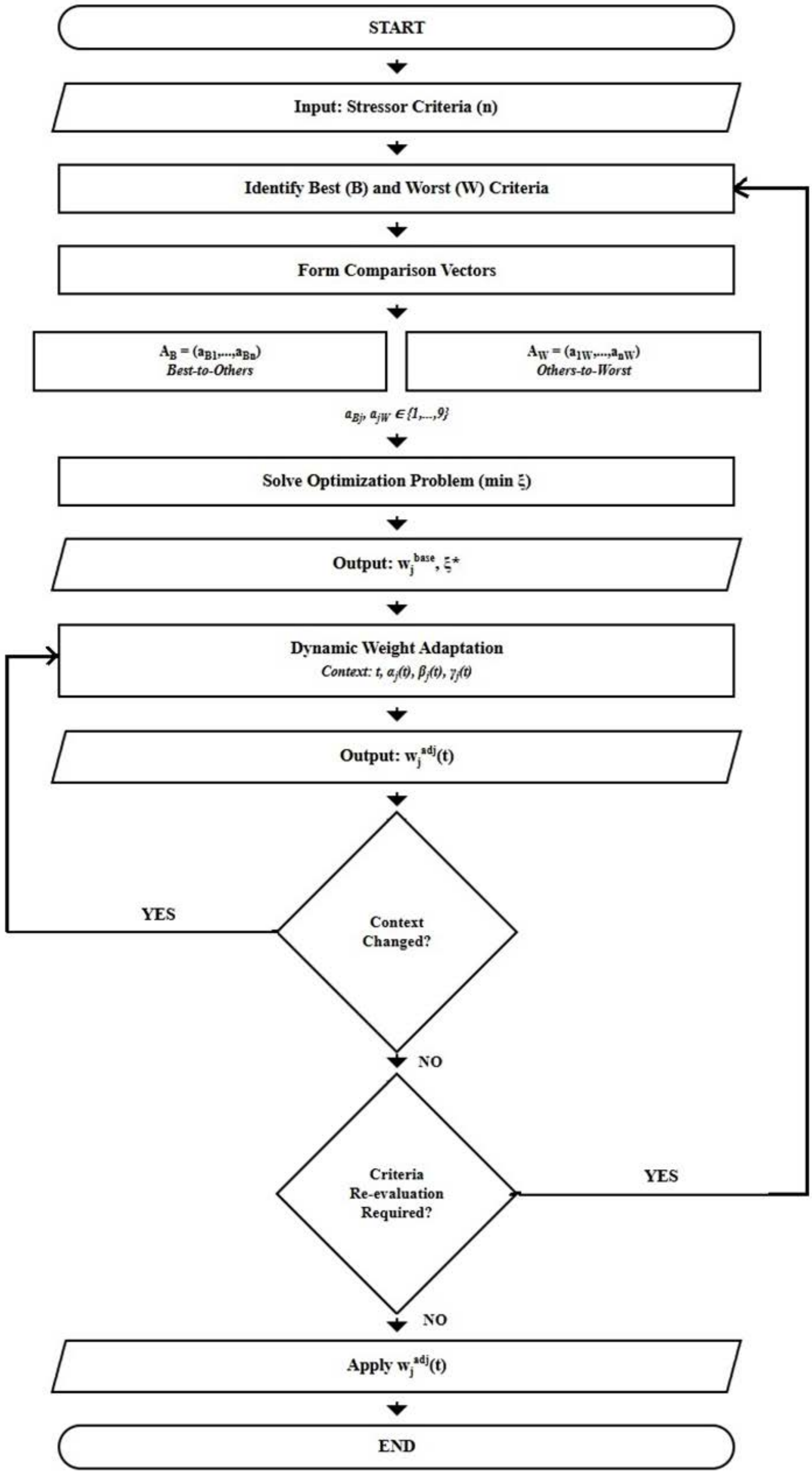

Fig. 4. BWM algorithm with dynamic weight adaptation

toward higher stress levels. Growth in JD(t) increases multipliers $\beta_j(t)$ for traffic/technical stressors and amplifies second-level rule sensitivity to "High/Very High" terms for these variables. Slow growth in BS(t) affects $\gamma_j(t)$, increasing weights of "fatigue" stressors at the end of the ATCO shift.

The defuzzification module employs five membership functions: Very Low (VL)/ Low (L)/Medium (M)/High (H)/Very High (VH). For example, for M-level:

$$\mu_{M(x)} = \left\{ \frac{x-40}{20}, 40 < x < 60; \frac{80-x}{20}, 60 \le x < 80; 0, \text{otherwise} \right\} \quad (8)$$

V and VH are defined similarly on intervals [60,80,100] and [80,100].

Membership function parameter updates in FIS are performed according to:

$$\theta_{new} = \theta_{old} - \alpha \nabla_{\theta L(\cdot)} \quad (9)$$

where θ_{old}, θ_{new} – membership function parameters before and after update; α – learning rate for membership function parameters $(10^{-4} - 10^{-2})$; $\nabla_{\theta L(\cdot)}$ – gradient of loss function L with respect to all parameters θ.

The stress management recommendation mechanism selects actions R (immediate/tactical/strategic) that minimize predicted deviation from target and cost:

$$R = \operatorname{argmin}_{R \in \mathcal{R}} \sum_{t=1}^{T} (L(S_t^R, S_{target}) + \lambda C(R)) \quad (10)$$

where R – selected recommendation (immediate/tactical/strategic); $\mathcal{R}$ – space of admissible reactive/proactive measure alternatives; t – time index (prediction step); T – prediction horizon length; S_t^R – predicted state (stress level) at time t; S_{target} – target state (desired/reference stress level); $L(S_t^R, S_{target})$ – loss function (measure of current/predicted state deviation from target); C(R) – cost (price/risks/resources) of executing action R: time, effort, workload impact; λ – weighting coefficient for trade-off between target achievement accuracy (L) and action cost (C).

Conclusions. The developed hybrid DSS represents a comprehensive approach to addressing the problem of ATCs' professional stress management through the integration of multi-criteria analysis methods, fuzzy logic, and machine learning. The proposed methodology for dynamic stressor weight adaptation ensures system flexibility and its ability to account for contextual changes in real-time, which is critically important for the dynamic air traffic services environment. The three-level FIS architecture enables effective aggregation of stressor impacts through five intermediate components while avoiding combinatorial rule explosion. The self-learning mechanism based on gradient descent ensures continuous improvement of assessment accuracy through automatic adjustment of membership function parameters and stressor weights according to accumulated experience.

Future research perspectives include: integration of additional biometric indicators to enhance stress assessment accuracy; expansion of the prediction module using recurrent neural networks to account for long-term dependencies; development of adaptive intervention strategies considering organizational constraints of specific ATC centers; investigation of deep learning methods application for automatic identification of new stress response patterns; validation of the developed system on real ATCO shift data from various airports; determination of unified metrics for evaluating the effectiveness of management interventions across different operational contexts.

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Пальоний А.С., Нечипуренко А.Г. ГІБРИДНА СИСТЕМА ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ ДЛЯ АДАПТИВНОЇ ОЦІНКИ ТА УПРАВЛІННЯ ПРОФЕСІЙНИМ СТРЕСОМ АВІАДИСПЕТЧЕРІВ У РЕАЛЬНОМУ ЧАСІ

Предметом дослідження статті є професійний стрес авіадиспетчерів, методологічні підходи до його багаторівневої оцінки та механізми управління в динамічному середовищі обслуговування повітряного руху. Дослідження зосереджено на розробці інтегрованої системи, що поєднує метод найкращого-найгіршого (BWM) для визначення ваг стресорів, багаторівневу нечітку систему виведення (FIS) для оцінки рівня стресу та модуль динамічної адаптації параметрів у реальному часі. Метою статті є побудова гібридної системи підтримки прийняття рішень для безперервної оцінки операційного стресу авіадиспетчерів із генеруванням персоналізованих рекомендацій втручання, що враховує динамічну природу стресорів, індивідуальні особливості диспетчерів та контекстуальні фактори робочого середовища. Завданнями статті є: систематизація та класифікація професійних стресорів авіадиспетчерів за джерелами виникнення; розробка методології динамічної адаптації ваг стресорів з урахуванням фази диспетчерської зміни, рівня повітряного руху та індивідуального профілю диспетчера; побудова трирівневої ієрархічної нечіткої системи виведення для агрегації впливу стресорів через п'ять компонентів-агрегаторів; формалізація механізму генерування оптимальних рекомендацій з управління стресом на основі прогнозування майбутніх станів системи. Методи дослідження включають: метод найкращого-найгіршого (BWM) для визначення базових ваг стресорів, нечітку логіку для моделювання невизначеності в оцінці стресу, градієнтний спуск для адаптації параметрів системи, системний аналіз для ідентифікації взаємозв'язків між компонентами. Отримані результати: розроблено функціональну модель DSS, представлену кортежем компонентів з формалізованими взаємозв'язками; запропоновано трифакторну модель динамічної адаптації ваг стресорів; побудовано алгоритм циклічного функціонування системи з інтервалом оновлення Δt=60 секунд; визначено структуру бази даних для збереження історії станів системи. Наукова новизна полягає в інтеграції методу BWM з механізмами динамічної адаптації для врахування контекстуальних змін у реальному часі, розробці трирівневої FIS для уникнення комбінаторного вибуху правил при збереженні точності оцінки, формалізації модулю самонавчання на основі градієнтного спуску для автоматичного налаштування параметрів системи відповідно до накопиченого досвіду. Практична значущість розробленої системи полягає в можливості її застосування для оперативного моніторингу стану авіадиспетчерів, прогнозування критичних ситуацій та формування обґрунтованих управлінських рішень щодо розподілу навантаження та організації роботи диспетчерських змін.

Ключові слова: *авіадиспетчер, професійний стрес, система підтримки прийняття рішень, нечітка логіка, динамічна адаптація, моніторинг у реальному часі.*

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