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DEVELOPMENT OF A MATHEMATICAL MODEL FOR THE ANALYSIS OF TIME SERIES OF PHYSIOLOGICAL PARAMETERS FOR A HOME MONITORING SYSTEM

РОЗРОБКА МАТЕМАТИЧНОЇ МОДЕЛІ ДЛЯ АНАЛІЗУ ЧАСОВИХ РЯДІВ ФІЗІОЛОГІЧНИХ ПАРАМЕТРІВ ДЛЯ СИСТЕМИ ДОМАШНЬОГО МОНІТОРИНГУ

The article considers the development of a mathematical model for the analysis of blood pressure time series in home monitoring settings. The proposed approach is based on decomposing the signal into three components: static level, variability, and dynamic trend. The algorithm utilizes non-linear penalty functions and the principle of aggregation by the most critical indicator to form an index of cardiovascular stability.

The verification of the algorithm was conducted through numerical simulation on synthetic time series replicating scenarios of undesirable trends, successful treatment, destabilization, and hypotension, as well as using a longitudinal real-world dataset covering 384 days of monitoring. The tests aimed to evaluate the index's sensitivity to structural signal changes and the model's ability to separate deterministic trends from measurement noise. The analysis indicates that the model allows for the identification of instability states that are not detected using traditional statistical averaging indicators. Specific technical limitations of the algorithm were identified, including a data aggregation period and the dependence of results on measurement regularity. The development is presented as a theoretical proposal for use within personal monitoring systems as an auxiliary tool for tracking state dynamics.

***Keywords**: home monitoring, blood pressure, time series analysis, mathematical modeling, trend, variability.*

У статті розглядається розроблення математичної моделі для аналізу часових рядів артеріального тиску в умовах домашнього моніторингу. Запропонований підхід базується на декомпозиції сигналу на три складові: статичний рівень, варіабельність та тренд. Алгоритм використовує нелінійні функції штрафу та принцип агрегації за найбільш критичним показником для формування індексу стабільності стану серцево-судинної системи.

Перевірка алгоритму здійснювалася шляхом чисельного моделювання на синтетичних часових рядах, що відтворювали сценарії небажаного тренду, успішного лікування, дестабілізації та гіпотензії, а також з використанням набору реальних даних домашнього моніторингу тривалістю 384 дні. Випробування були спрямовані на оцінку чутливості індексу до структурних змін сигналу та здатності моделі відокремлювати детерміновані тренди від вимірювального шуму. За результатами аналізу встановлено, що модель дозволяє фіксувати стани нестабільності, які не виявляються

при використанні традиційних статистичних показників усереднення. Визначено технічні обмеження алгоритму, зокрема період накопичення даних та залежність результатів від регулярності вимірювань. Розробка представлена як теоретична пропозиція для використання у складі систем персонального моніторингу як допоміжний інструмент відстеження динаміки показників.

***Ключові слова**: домашній моніторинг, артеріальний тиск, аналіз часових рядів, математичне моделювання, тренд, варіабельність.*

Problem's Formulation

Cardiovascular diseases remain the dominant cause of mortality worldwide, with arterial hypertension acting as a key risk factor. Today, the strategy for controlling this condition is undergoing substantial transformations, shifting the emphasis from episodic visits to the doctor to systematic home monitoring. Due to the widespread distribution of digital blood pressure monitors and the possibility of automatic synchronization of measurements, patients have gained a tool for the independent accumulation of significant arrays of data regarding their own hemodynamics.

However, this very increase in information volumes has actualized the problem of its objective interpretation. In conditions of ambulatory use, in the absence of direct supervision by a specialist, it is difficult for the user to adequately assess the array of unstructured data. The majority of algorithms implemented in modern software solutions operate according to a simplified scheme, relying on generalized statistical indicators. Such an approach provides only a static snapshot of the patient's condition, disregarding the dynamics of changes over time, which significantly reduces the diagnostic value of monitoring.

Relying exclusively on averaged data, we lose the opportunity to track the real development of the pathological process. This creates the risk that premorbid states, characterized by hidden instability with formally normal indicators, will remain unnoticed. In this regard, there arises an urgent need for the development of adaptive mathematical models for home monitoring systems capable of automating the analysis of time series and ensuring an integral assessment of the patient's stability.

Analysis of recent research and publications

In medical research, the thesis regarding the insufficiency of episodic visits to the doctor runs as a common thread. Specialists emphasize in their publications that regular self-monitoring of blood pressure in home conditions is critically important for the effective management of the disease and the prevention of complications. This opinion is also confirmed by international studies, where the advantage of home monitoring over clinical monitoring is proven due to the ability to obtain large arrays of data in an environment habitual for the patient [1].

Of particular interest are studies that focus not simply on the level of blood pressure, but on its dynamics. Sources indicate that day-to-day variability of indicators has high prognostic value. It has been proven that patients with high blood pressure instability have significantly higher risks of cardiovascular events, even if their average indicators are within the normal range [2]. This fundamentally changes the approach to information processing: instead of static averaging, there arises a need for dynamic assessment that considers both the intensity of deviations and the general trend of the process development.

In parallel with medical justifications, technical means of monitoring support are actively developing. Publications dedicated to telemedicine technologies consider organizational models of remote patient supervision. Authors note that the use of modern information systems allows improving the interaction between doctor and patient and increasing adherence to treatment [3].

From an engineering point of view, significant attention is paid to the architecture of such systems. Works on computer-integrated technologies describe in detail the methods for the collection, transmission, and storage of data obtained from personal devices [4]. However, an analysis of these sources reveals a certain gap: existing technical solutions mostly solve the task of data transportation and visualization. The algorithmic component is often limited to basic statistics or the recording of threshold value exceedances, not fully utilizing the potential of variability and dynamics analysis, the importance of which is insisted upon by medical research.

Formulation of the study purpose

The purpose of the paper is to present a mathematical model designed for the analysis of arterial blood pressure time series within home monitoring systems. The objectives of the study are as follows: to develop an algorithmic approach for decomposing the monitoring signal into components of static

level, variability, and dynamic trend, to formulate a mechanism for aggregating these components into an index of cardiovascular stability, and to conduct a numerical experiment using synthetic and longitudinal real-world datasets to evaluate the model's sensitivity and identify its technical limitations.

Presenting main materials

The primary objective of this work is the development of a mathematical model for home monitoring systems that allows for the automation of the interpretation of hemodynamic data and the reduction of a complex array of measurements to a single quantitative integral assessment (index). This indicator is intended for the quantitative characterization of the current stability of the patient's cardiovascular system, detecting hidden risks at early stages. The proposed approach envisages the calculation of a general assessment based on the analysis of a discrete time series of measurements obtained using personal digital devices.The basis for performing calculations is a discrete time series of measurements obtained with the help of personal digital devices.

The input dataset is formalized in the form of two vectors: systolic pressure and diastolic pressure , defined on a set of time moments T. The analysis of this data is performed using the sliding window method. To ensure an optimal balance between sensitivity to new changes in health status and the statistical reliability of results, the depth of analysis for calculating the current index value is 30 days. Such a time horizon allows for neutralizing the influence of random isolated outliers and measurement noise, while preserving the ability to detect systemic shifts. The research hypothesis is that an objective assessment of the hemodynamic state must rely on the analysis of the entire structure of the measurement time series, as this allows for taking into account the multifactorial structure of risks, which includes the level, variability, and dynamics of the process.

Therefore, the general integral assessment $I(t)$ is considered as a composition of three components, each of which corresponds to a separate aspect of the physiological process. The first component, the level component (I_{Level}), evaluates the measure of deviation of absolute values from target norms and the accumulated static load on the vessels. The second component, the variability component ($I_{Variability}$), characterizes the stability of pressure regulation mechanisms and the day-to-day spread of values. The third component, the trend component ($I_{Dynamic}$), is intended for the detection of long-term trends of condition deterioration. Formally, the general assessment at time moment t is determined by the aggregation function of these three normalized sub-indices. The result of the calculation is a dimensionless quantity in the range $[0,1]$, where a value of 1.0 corresponds to a stable physiological state, and an approach to 0.0 indicates a destabilization of the system and an increase in the probability of cardiovascular events. Below is a sequential presentation of each component of the general index. The first and fundamental component of the model is the static level index (I_{Level}), intended for the assessment of the patient's basic hemodynamic status based on data analysis for a sliding window with a duration of $T = 30$ days. Unlike traditional arithmetic averaging of indicators, the calculation algorithm is based on the concept of cumulative load, where each measurement is evaluated through the prism of a quadratic penalty function. This allows for realizing a non-linear dependence of risk on the magnitude of deviation: minor physiological fluctuations within the target range (100–120 mmHg for systolic and 60–80 mmHg for diastolic pressure) generate zero or minimal penalty, while pronounced deviations lead to an exponential increase in the danger indicator. To account for the clinical asymmetry of risks, a coefficient $K_{asym} = 1.5$ has been introduced, which is applied exclusively to cases of exceeding the upper limit of the norm, mathematically establishing the priority of hypertension over hypotension of similar amplitude.

The calculation of the instantaneous penalty P_{inst} for the i-th measurement is performed taking into account the physiological features of pulse pressure. Considering the different amplitude of pathological fluctuations, the system uses differentiated weighting of components. For systolic pressure, characterized by high natural variability, the weighting coefficient is $W_{SBP} = 1.0$. For diastolic pressure, which has a significantly narrower range of changes (where an increase of 40 units is critical, unlike 60-70 units for systolic), the sensitivity of the model is increased twofold ($W_{DBP} = 2.0$). This allows for aligning the clinical weight of both parameters in the structure of total risk [5]. The formalized calculation of the weighted penalty for each measurement looks as follows:

$$P_{inst}^{(i)} = W_{param} \cdot (y_i - T_{max})^2 \cdot K_{asym}, \quad \text{when } y_i > T_{max}; \tag{1}$$

$$P_{inst}^{(i)} = W_{param} \cdot (T_{min} - y_i)^2, \quad \text{when } y_i < T_{min}; \tag{2}$$

$$P_{inst}^{(i)} = 0, \quad \text{при } T_{min} \le y_i \le T_{max}. \tag{3}$$

Time aggregation of the obtained penalties is performed using the Exponentially Weighted Moving Average method with a decay coefficient $\lambda = 0.95$. This approach ensures the priority of current data: measurements taken today have greater weight than those taken at the beginning of the observation window, yet the full history continues to form a stable trend. Individual indices I_{param} for systolic and diastolic pressure are obtained by normalizing the weighted sum of penalties relative to the maximum calculated saturation limit $P_{max} = 2500.0$:

$$I_{param} = 1 - \frac{\sum_{i=1}^{N} \lambda^{\Delta t_i} \cdot P_{inst}^{(i)}}{P_{max} \cdot \sum_{i=1}^{N} \lambda^{\Delta t_i}}, \quad (4)$$

where Δt_i is the time interval in days between the current moment and the i-th measurement. The use of a single denominator P_{max} in combination with double weight for diastolic pressure lowers the saturation threshold for the latter, guaranteeing that diastolic hypertension of 115 mmHg will be evaluated as the same critical condition (index ≈ 0) as systolic hypertension of 170 mmHg. A key feature of the final stage of the algorithm is the rejection of additive averaging of components. Aggregation into the general index I_{Level} implements the conservative principle of the weakest link (min-aggregation):

$$I_{Level} = \min(I_{SBP}, I_{DBP}). \quad (5)$$

Such logic is based on the clinical axiom that isolated systolic or diastolic hypertension are independent risk factors. A normal level of one of the indicators cannot compensate for the pathological impact of the other; therefore, the system automatically adapts to the hemodynamic component that is in the most critical state, which precludes the masking of the problem.

The next stage of analysis is the assessment of the time series variability. Traditional clinical monitoring, focusing primarily on mean blood pressure values, often overlooks the dynamic nature of cardiovascular regulation. At the same time, the accumulated evidence base convincingly demonstrates that blood pressure variability (BPV) is a powerful and independent predictor of pathological states, the influence of which persists even with a normalized mean pressure level. According to the results of long-term studies, high variability is associated not only with organ damage but also acts as a significant risk factor for cognitive impairments. In particular, a linear relationship between the increase in systolic variability and the risk of dementia has been proven [6].

Moreover, data from ambulatory monitoring and home measurements confirm that pressure fluctuations have independent prognostic value regarding all-cause mortality and cardiovascular events, which extends beyond the informativeness of standard averaged indicators [7]. Thus, the component I_{Var} has been integrated into the structure of the general index. Its goal is to quantitatively characterize data dispersion and identify the hidden instability of the process.

Detrended standard deviation (SD) was selected as the basic dispersion metric. Unlike classical SD, which calculates the deviation from the arithmetic mean, this method preliminarily approximates the data with a linear trend function and calculates the variance of residuals — the differences between real values and the trend line.

$$SD_{detrended} = \sqrt{\frac{\sum\left(y_i - (at_i + b)\right)^2}{N - 1}}. \quad (6)$$

Such an approach allows avoiding the problem of double penalty, when a patient with a smooth yet pronounced change in pressure (trend) is erroneously classified as one possessing high chaotic variability. The penalty function $v_p(t)$ reflects the degree of proximity of the variability to the critical limit and is calculated using the method of linear interpolation with limitation in the range $[0,1]$:

$$v_p(t) = 1 - \min\left(1, \max\left(0, \frac{SD_p(t) - \tau_{min}}{\tau_{max} - \tau_{min}}\right)\right). \quad (7)$$

Thus, the value $v_p = 1$ corresponds to the physiological norm of stability, and $v_p = 0$ — to critical instability. The calibration of normalization ranges $[\tau_{min}, \tau_{max}]$ was performed empirically based on data from population studies of variability. For systolic pressure, a corridor of $[7.0,18.0]$ mmHg is established, where the upper limit correlates with the upper quintile of the SD distribution associated with an increase in cardiovascular risks. For diastolic pressure, the stability of which is more critical for myocardial perfusion, the range is narrower and amounts to $[5.0,12.0]$ mmHg.To form the final variability index I_{Var}, the conservative aggregation principle based on the weakest link method (min-aggregation) is applied [5].

The choice of this strategy is dictated by the necessity to avoid the risk masking effect, when critical instability of one parameter can be neutralized by the stability of another. Such an approach guarantees that the resulting assessment will reflect the state of the most vulnerable link of hemodynamics. Thus, the integral index is determined by the worst stability indicator among the components:

$$I_{Variability}(t) = \min\left(v_{SBP}(t), v_{DBP}(t)\right). \quad (8)$$

The obtained indicator allows for quantitatively assessing the efficiency of the patient's regulatory mechanisms: a decrease in I_{Var} indicates an increase in the chaotic nature of hemodynamics, which requires clinical attention even under conditions of normal mean pressure values.

To understand the logic of the dynamics index ($I_{Dynamic}$), it is important to consider it not as an instantaneous assessment of the state, but as a recurrent risk integrator. Unlike static indicators, this index operates on the principle of accumulating penalty points, which allows the system to "remember" the duration and intensity of negative trends. The calculation process begins with the detection of the deterministic drift of blood pressure on a sliding window with a duration of $T = 45$ days. For this, the least squares method is applied, which allows constructing an approximating linear function:

$$y = a + b \cdot t, \quad (9)$$

where parameter b reflects the rate of change of the indicator (mmHg/day), and t is the time in days from the beginning of observation. Each recorded change generates a risk impulse J, the magnitude of which depends on the rate of the trend b. These impulses are not simply displayed on the graph, but are added to the total sum of the accumulated penalty P, forming the dynamic history of the patient's condition. The basic logic of accumulation is described by a recurrent equation, where the current value of the penalty $P_{current}$ depends on its previous state and the new impulse:

$$P_{current} = P_{previous} \cdot r + J. \quad (10)$$

In this model, penalty accumulation is regulated by two critical mechanisms: the rate of risk "forgetting" (coefficient r) and the maintenance of a minimum permissible alarm level. The necessity of using a dynamic decay coefficient r instead of a constant is conditioned by the need to model the system's physiological memory (clinical hysteresis). This means that the index recovery time must directly depend on the severity of the previous state. The coefficient r determines which part of the accumulated penalty carries over to the next step. If the patient's indicators are close to normal, r decreases, accelerating recovery. With significant deviations from the target level (y_{target}), the coefficient increases, slowing down the clearing of the penalty and holding the index at low values. Mathematically, this mechanism is implemented through a limiting function:

$$r = \max\left(r_{min}, \min\left(R + \frac{|y - y_{target}| - 10}{M}, r_{max}\right)\right), \quad (11)$$

where $R = 0.94$ is the basic inertia, and $r_{max} = 0.995$ is the limit of "long-term memory" for severe pathologies. The parameter $M = 600$ regulates the sensitivity of this inertia to deviations from the target level (110 mmHg for systolic pressure). The second regulator is the mechanism of the irreducible threshold of cumulative risk (P_{base}). It was introduced to address the problem of the plateau effect, when blood pressure stabilizes at high values and stops rising. Since in such a case the rate of change b becomes zero, without this mechanism, the index could erroneously return to unity. P_{base} sets an irreducible penalty limit that depends on the absolute pressure value:

$$P_{base} = \max(0, (y - y_{max}) \cdot F), \quad (12)$$

where $y_{max} = 120$ mmHg, and $F = 1.25$ is the proposed inertia coefficient. Thus, the final formula for calculating the accumulated penalty takes into account both the dynamics of change and the current danger of the level:

$$P_{current} = \max\left(P_{base}, P_{previous} \cdot r + J\right). \quad (13)$$

For the final assessment, the values of the penalties of the systolic and diastolic components are aggregated according to the principle of dominance of the most critical indicator. The obtained result is converted into the scale $[0,1]$ using a logistic saturation function:

$$I_{Dynamic} = \left(1 + \frac{\max(P_{SBP}, P_{DBP})}{S}\right)^{-1}. \quad (14)$$

The proposed constant $S = 50.0$ determines the steepness of the index decline during destabilization. All presented parameters are empirical and require further verification.

The final stage of the model's operation consists in the synthesis of the calculated sub-indices—level (I_{Level}), variability ($I_{Variability}$), and dynamics ($I_{Dynamic}$) — into a single scalar indicator of the cardiovascular system state, denoted as I. For the aggregation of components, the method of weighted Euclidean risk aggregation is applied. This approach is based on the transformation of each index ($I \in [0,1]$) into a component of the risk vector $R_k = 1 - I_k$. The general risk of the system is defined as the ratio of the length of the weighted vector of current risks to the maximum possible length of the vector (the theoretical maximum, when all indicators equal zero). Formally, the calculation is performed according to the following algorithm:

$$R_{Total}(t) = \frac{\sqrt{\left(W_L \cdot R_{Level}(t)\right)^2 + \left(W_D \cdot R_{Dynamic}(t)\right)^2 + \left(W_V \cdot R_{Var}(t)\right)^2}}{\sqrt{W_L^2 + W_D^2 + W_V^2}}; \quad (15)$$

$$I(t) = 1 - R_{Total}(t). \quad (16)$$

The use of the Euclidean norm implements the weakest link principle: a significant increase in risk in any of the components has a disproportionately large influence on the length of the resulting vector. This allows avoiding the situation where a critical problem in one area (for example, a sharp negative trend) is completely masked by ideal values of other indicators, which is critically important for medical alert systems. The distribution of weighting coefficients in this model is an approximate assessment of the contribution of each factor to the patient's general condition. The greatest weight is assigned to the level component ($W_L = 0.4$), since absolute blood pressure values remain the primary diagnostic criterion. The dynamics ($W_D = 0.30$) and variability ($W_V = 0.3$) components are given slightly lower priority and are equal to the same value. To ensure statistical reliability, a staging of calculations is implemented in the algorithm. The calculation of indices begins only after the accumulation of a minimum observation period of 30 days ($t \geq 30$). In the transitional period (from the 30th to the 90th day), when the assessment of the long-term trend is not yet technically possible, the dynamics component is considered neutral ($I_{Dynamic} = 1.0$, $R_{Dynamic} = 0$). This allows the system to provide a valid assessment based on level and variability as early as the first month, automatically engaging trend analysis as a sufficient volume of historical data accumulates.

The validation of the proposed algorithm was performed using numerical simulations on synthetic time series representing typical data patterns, as well as on a longitudinal real-world dataset. The primary objective of the experiment was to evaluate the index's sensitivity to various signal disturbances and to verify the correctness of the inertia and aggregation mechanisms.

Analysis of the unwanted trend scenario (Fig. 1) illustrates the model's response to a monotonic drift in system parameters, where systolic pressure gradually deviates from an initial baseline of 140 mmHg to 155 mmHg. A distinguishing feature of this simulation is the behavior of the dynamic trend component ($I_{Dynamic}$), which maintains consistently low values throughout the observation period. This suppression results from the detection of a persistent positive slope in the linear regression model ($b > 0$) combined with high absolute values, which triggers the algorithm's specific penalty for risk acceleration; the model identifies that the system is not only outside the homeostatic range but is actively deteriorating. Concurrently, the static level index (I_{Level}) exhibits a steady decline proportional to the increasing squared distance from the target range, while the variability index ($I_{Variability}$) remains at unity, correctly filtering out the constant background noise. This decoupling confirms the algorithm's ability to differentiate between deterministic vector changes and stochastic volatility, resulting in a final index (I_{Final}) that accurately reflects the cumulative burden of the progressing pathology.

The analysis of the successful treatment scenario (Fig. 2) demonstrates the system's response to a therapeutic intervention where systolic pressure monotonically declines from a hypertensive baseline of 160 mmHg to a target value of 115 mmHg. A critical observation in this simulation is the distinct decoupling between the restoration rates of the static level (I_{Level}) and dynamic trend ($I_{Dynamic}$) components. While I_{Level} responds elastically, reaching near-maximum values immediately upon the signal's entry into the normotensive range, the Dynamic index exhibits a programmed inertia, lagging significantly behind the physiological improvement. This behavior is the direct result of the adaptive decay coefficient, which enforces a clinical memory effect; the model continues to penalize the system for the recent history of

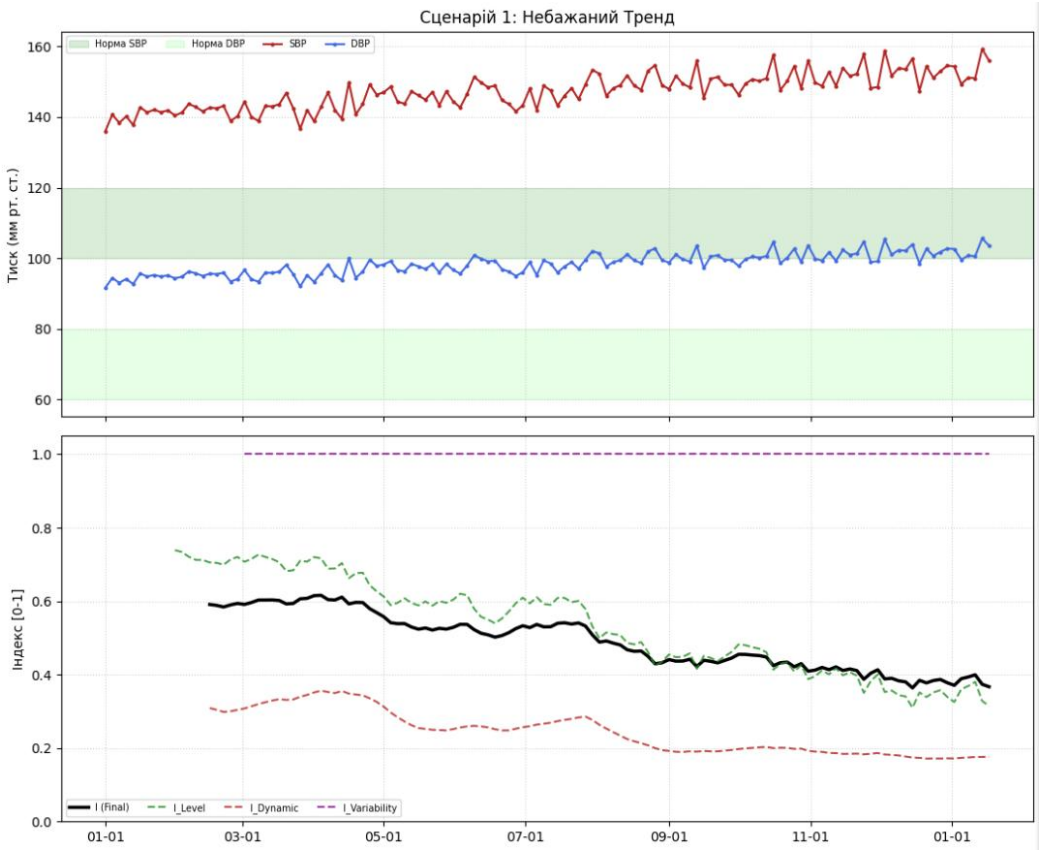

Fig. 1. Unwanted trend scenrio analysis

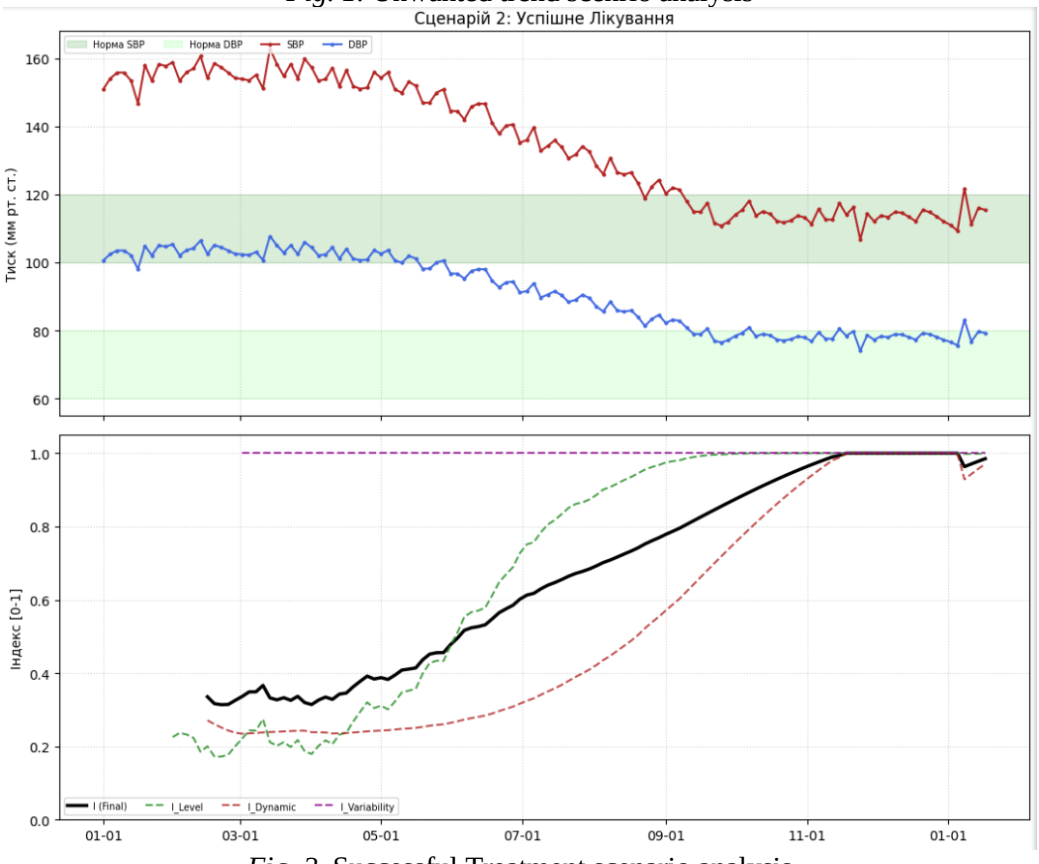

Fig. 2. Successful Treatment scenario analysis

instability even after absolute values have normalized. Consequently, the final index (I_{Final}) rises gradually rather than instantaneously, implementing a probationary period that prevents the premature classification of the patient as stable until the remission is proven to be sustained.

The analysis of the destabilization scenario (Fig. 3) highlights the critical limitation of monitoring approaches based solely on central tendency metrics. In this simulation, while the mean systolic pressure remains within a consistent range —reflected by the relatively high and stable values of the static level component — the system introduces high-amplitude stochastic fluctuations. The model reacts instantaneously to the structural change in the signal: the variability index exhibits a precipitous decline from unity to critical values. It is observed that following this acute shock, the index displays a slight partial recovery as the sliding window adapts to the new regime, yet it stabilizes at a suboptimal plateau. The final index (I_{Final}) is forcibly depressed, signaling a high-risk state.

Fig. 3. Destabilization scenario analysis

The simulation of the progressive hypotension scenario (Fig. 4) validates the model's capacity to handle lower-bound boundary violations, confirming the universality of the quadratic penalty function. As the systolic pressure exhibits a monotonic decline from a normotensive baseline to values below the physiological threshold of 90 mmHg, the static level index demonstrates a symmetric penalty response comparable to that of hypertensive deviations. A distinguishing characteristic of this trial is the predictive behavior of the dynamic trend component, which registers a sharp decline during the early phase of the drift, anticipating the breach of the target range before it strictly occurs based on the trajectory's negative slope. Meanwhile, the variability index stays equal to 1, ignoring negative trend and fluctuations. This confirms that the algorithm functions as a bidirectional safety monitor, treating hypotensive excursions with the same critical weight as hypertensive crises, while the trend component provides a predictive warning of the impending state degradation.

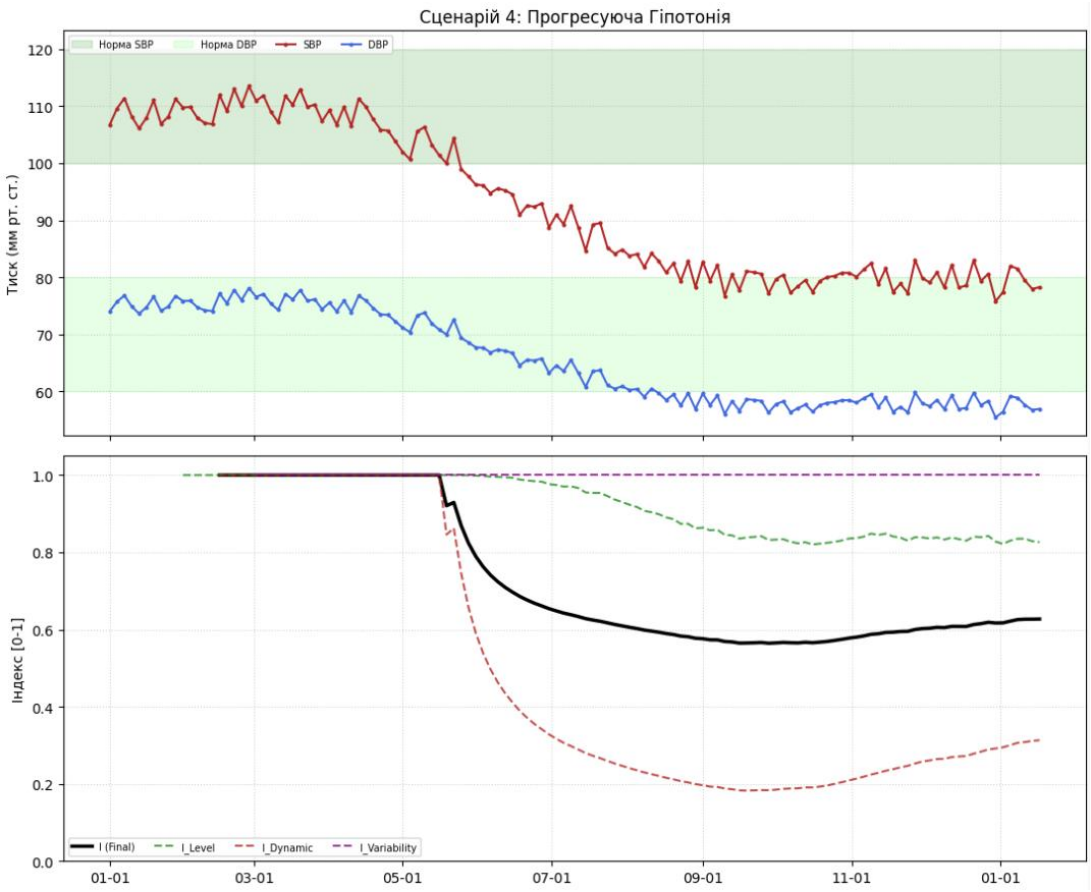

Fig. 4. Progressive hypotension scenario analysis

The empirical validation was conducted using a longitudinal dataset obtained from a 67-year-old male subject with a documented history of atherosclerosis. Home blood pressure monitoring was performed using a semi-automatic device following a standardized protocol: measurements were taken on a bare arm following physiological relief, consisting of the arithmetic mean of three consecutive trials separated by one-minute intervals, with a discrete sampling frequency of one session every three days over a total duration of 384 days ($N = 128$) [8]. The analysis of this real-world time series (Fig. 5) demonstrates the algorithm's capacity to process data characterized by intrinsic high-frequency noise and non-stationarity. Unlike synthetic scenarios, this signal exhibits continuous stochastic fluctuations without a single deterministic trend; however, the final index successfully functions as a low-pass filter, generating a smoothed trajectory that reflects the macroscopic state of the system while ignoring isolated outliers. Notably, while the variability component fluctuates significantly, reflecting periods of relative stability versus volatility, the final index remains dominated by the consistently critical values of the static level driven by sustained systolic pressure above 150 mmHg. This confirms the robustness of the weighted Euclidean aggregation strategy in a clinical setting: by treating risk components as vectors, the algorithm ensures that the chronic high-magnitude deviation in the static level disproportionately influences the total score, prioritizing sustained hypertension over temporary improvements in signal variance and providing a conservative, reliable assessment.

Conclusions

The research presented in this paper proposes a mathematical model designed to analyze long-term blood pressure data collected at home. Instead of relying solely on simple averages, the algorithm breaks down the monitoring signal into three distinct parts: static level, trend and variability. By looking at these different aspects separately, the model can identify risk patterns even when the average blood pressure numbers appear normal.

Fig. 5. Real-world home measurements scenario analysis

The resulting index is calculated as the norm of the state vector in a three-dimensional feature space, where the coordinates correspond to the values of the component metrics. In the aggregation process, a non-linear preference function is applied, assigning dominant weight to the component with the maximum deviation amplitude. This ensures the model's sensitivity to any disturbance of the normal state, preventing the masking of pathological patterns by averaged values. Additionally, the model incorporates a memory effect: the state assessment does not improve instantaneously following a pressure reduction. Instead, the index adjusts gradually, ensuring the stability of recovery before a positive conclusion is formed.

However, the current implementation has specific limitations. Because the algorithm relies on analyzing long-term trends and variability windows, it suffers from a "cold start" problem; it requires about two months of accumulated data to generate a fully accurate analysis. This makes the method suitable for long-term observation but not for immediate use in acute situations. Additionally, the mathematical settings (thresholds and weights) used in this study are general estimates. Since every person is different, these settings might need automatic adjustment to work perfectly for everyone. The system also requires regular measurements to be effective, as large gaps in the data can distort the calculation of trends.

Consequently, this algorithm is presented as a theoretical proposal intended for integration into home health monitoring systems. Its primary objective is to transform raw, long-term blood pressure records into approximate, interpretable estimates, helping users visualize trends that are difficult to see in a simple list of numbers.

References

[1] Weinfeld, J. M., Hart, K. M., & Vargas, J. D. (2021). Home Blood Pressure Monitoring. American family physician, 104(3), 237-243.

[2] Chenkai Wu , Michael G. Shlipak , Robert S. Stawski , Carmen A. Peralta , Bruce M. Psaty , Tamara B. Harris , Suzanne Satterfield , Eric J. Shiroma , Anne B. Newman , Michelle C. Odden. Visit-to-Visit Blood Pressure Variability and Mortality and Cardiovascular Outcomes Among Older Adults:

The Health, Aging, and Body Composition Study, American Journal of Hypertension, Volume 30, Issue 2, 1 February 2017, Pages 151-158, https://doi.org/10.1093/ajh/hpw106
[3] Bulda, V. I., Bohomaz, V. M., & Berdnyk, I. O. (2019). Vykorystannia telemedychnykh tekhnolohii u menedzhmenti arterialnoi hipertenzii [The use of telemedicine technologies in the management of arterial hypertension]. Visnyk Problem Biolohii i Medytsyny, 1(2), 20–24. https://doi.org/10.29254/2077-4214-2019-1-2-149-20-24
[4] Fedoniuk, I. A. (2024). Mobilnyi zastosunok informatsiino-tekhnolohichnoho suprovodu liudei iz hipertonichnymy zakhvoriuvanniamy [Mobile application for information and technological support for people with hypertensive diseases]. Kompiuterno-intehrovani Tekhnolohii: Osvita, Nauka, Vyrobnytstvo, (56), 283–291. https://doi.org/10.36910/6775-2524-0560-2024-56-36
[5] Mancia, G., Kreutz, R., Brunstr, M., Burnier, M., Grassi, G., Januszewicz, A., Muiesan, M. L., Tsioufis, K., Agabiti-Rosei, E., Algharably, E. A. E., Azizi, M., Benetos, A., Borghi, C., Hitij, J. B., Cifkova, R., Coca, A., Cornelissen, V., Cruickshank, J. K., Cunha, P. G., Danser, A. H. J., ,Äö√Ñ Kjeldsen, S. E. (2023). 2023 ESH Guidelines for the management of arterial hypertension The Task Force for the management of arterial hypertension of the European Society of Hypertension: Endorsed by the International Society of Hypertension (ISH) and the European Renal Association (ERA). Journal of hypertension, 41(12), 1874-2071. https://doi.org/10.1097/HJH.0000000000003480
[6] Kulkarni, S., Parati, G., Bangalore, S., Bilo, G., Kim, B. J., Kario, K., Messerli, F., Stergiou, G., Wang, J., Whiteley, W., Wilkinson, I. B., & Sever, P. (2025). Blood pressure variability: a review. Journal of Hypertension, 43(6), 929-938. https://doi.org/10.1097/HJH.0000000000003994
[7] Haverkamp, R. A., Melis, R. J. F., Claassen, J. A. H. R., & de Heus, R. A. A. (2022). Day-To-Day Home Blood Pressure Variability and All-Cause Mortality in a Memory Clinic Population. Journal of Alzheimer's disease : JAD, 85(3), 1219-1231. https://doi.org/10.3233/JAD-215002
[8] Trends and seasonality extracting from Home Blood Pressure Monitoring readings. (2017). Mendeley data. https://data.mendeley.com/datasets/pjcv33hpp7/1

Список використаної літератури

1. Weinfeld J. M., Hart K. M., Vargas J. D. Home Blood Pressure Monitoring. American Family Physician. 2021. Vol. 104, No. 3. P. 237–243.
2. Wu C., Shlipak M. G., Stawski R. S. et al. Visit-to-Visit Blood Pressure Variability and Mortality and Cardiovascular Outcomes Among Older Adults: The Health, Aging, and Body Composition Study. American Journal of Hypertension. 2017. Vol. 30, Iss. 2. P. 151–158. DOI: https://doi.org/10.1093/ajh/hpw106.
3. Бульда В. І., Богомаз В. М., Бердник І. О. Використання телемедичних технологій у менеджменті артеріальної гіпертензії. Вісник проблем біології і медицини. 2019. Вип. 1, Т. 2 (149). С. 20–24. DOI: https://doi.org/10.29254/2077-4214-2019-1-2-149-20-24.
4. Федонюк Ю. А. Мобільний застосунок інформаційно-технологічного супроводу людей із гіпертонічними захворюваннями. Комп'ютерно-інтегровані технології: освіта, наука, виробництво. 2024. Вип. 56. С. 283–291. DOI: https://doi.org/10.36910/6775-2524-0560-2024-56-36.
5. Mancia G., Kreutz R., Brunström M. et al. 2023 ESH Guidelines for the management of arterial hypertension. Journal of Hypertension. 2023. Vol. 41, No. 12. P. 1874–2071. DOI: https://doi.org/10.1097/HJH.0000000000003480.
6. Kulkarni S., Parati G., Bangalore S. et al. Blood pressure variability: a review. Journal of Hypertension. 2025. Vol. 43, No. 6. P. 929–938. DOI: https://doi.org/10.1097/HJH.0000000000003994.
7. Haverkamp R. A., Melis R. J. F., Claassen J. A. H. R., de Heus R. A. A. Day-To-Day Home Blood Pressure Variability and All-Cause Mortality in a Memory Clinic Population. Journal of Alzheimer's Disease : JAD. 2022. Vol. 85, No. 3. P. 1219–1231. DOI: https://doi.org/10.3233/JAD-215002.
8. Trends and seasonality extracting from Home Blood Pressure Monitoring readings [Electronic resource]. Mendeley Data. 2017. URL: https://data.mendeley.com/datasets/pjcv33hpp7/1.

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