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HYBRID MULTIPLICATIVE AGGREGATION MODEL FOR LONG-TERM CONSUMER PRICE INDEX FORECASTING

This article improves the forecasting toolkit for the Consumer Price Index under conditions of macroeconomic uncertainty. The study proposes a hybrid approach based on cross-verification of heterogeneous data and fuzzy logic. The mathematical core of the model utilizes the Bellman-Zadeh multiplicative synthesis scheme, which eliminates the risk compensation effect and enhances sensitivity to hidden economic shocks. The proposed methodology successfully handles nonlinear volatility and reduces data asymmetry across various international and national statistical sources. Research results confirm the model's high reliability in identifying «grey zones» and transitional inflationary phases, thereby enabling a shift from reactive monitoring to proactive adaptation through a possibility degree for 2025-2026 economic scenarios within a scalable framework adaptable to other interconnected socio-economic systems.

Keywords: *Consumer Price Index, fuzzy logic, Bellman-Zadeh scheme, macroeconomic forecasting, multiplicative synthesis, adaptive modeling.*

JEL classification: *C44, C53, E31, E37.*

ГІБРИДНА МОДЕЛЬ МУЛЬТИПЛІКАТИВНОЇ АГРЕГАЦІЇ ДЛЯ ДОВГОСТРОКОВОГО ПРОГНОЗУВАННЯ ІНДЕКСУ СПОЖИВЧИХ ЦІН

Актуальність дослідження зумовлена необхідністю модернізації прогнозного інструментарію оцінки інфляційних процесів в умовах високої макроекономічної невизначеності. Метою роботи є розробка та вдосконалення методичного підходу до оцінювання індексу споживчих цін на основі інтеграції гібридних даних та апарату нечіткої логіки, що дозволяє формалізувати неочевидні закономірності в динаміці цін. Методологічна база роботи містить системне поєднання методів інтелектуального аналізу даних та економіко-математичного моделювання. Інструменти інтелектуального аналізу забезпечують якісну попередню обробку та верифікацію гетерогенних статистичних масивів у режимі реального часу. На цій основі апарат економіко-математичного моделювання, що базується на нечіткій логіці, дозволяє формалізувати нелінійні взаємозв'язки між показниками та трансформувати кількісні дані у стратегічні управлінські сценарії. У роботі застосовано підхід перехресної верифікації гетерогенних часових рядів для формування валідованого масиву показників. Математична формалізація синтезу базується на схемі Беллмана-Заде з використанням трикутних функцій належності та мультиплікативної згортки, що забезпечує чутливість моделі до прихованих ризиків. У результаті дослідження розроблено гібридну модель, яка дозволяє ідентифікувати перехід системи у зони невизначеності та оцінювати ступінь можливості реалізації макроекономічних сценаріїв. Ретроспективна верифікація підтвердила достовірність моделі в ідентифікації шокових станів та її спроможність адекватно відтворювати структурні зміни в динаміці цін. Запропонований підхід дозволяє менеджменту трансформувати стратегію управління з реактивної на проактивну. Практична значущість результатів полягає у створенні аналітичного інструментарію для переходу від пасивного моніторингу інфляційних процесів до превентивної адаптації управлінських рішень. Модель може бути інтегрована в систему стратегічного планування як функціональний елемент антикризового управління, що дозволяє мінімізувати часовий лаг між виникненням сигналу про дестабілізацію та впровадженням відповідних коригувальних заходів.

Ключові слова: *індекс споживчих цін, нечітка логіка, схема Беллмана-Заде, макроекономічне прогнозування, мультиплікативний синтез, адаптивне моделювання.*

Formulation of the problem. Developing long-term economic models primarily requires formalizing their stochastic parameters and verifying the criteria that drive strategic development. The choice of methods for analyzing such systems directly depends on the level of uncertainty. Whereas traditional approaches mostly depended on expert methods-with choices driven by specialist intuition and experience-contemporary conditions demand the integration of such knowledge with big data analysis. The legitimacy of relying solely on subjective assessments rests on the

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assumed reliability of a generalized collective judgment; here, an individual expert evaluation is treated as a realization of a random variable, while the group judgment serves as a reliable benchmark. However, this assumption frequently proves invalid when applied to long-term economic forecasting, specifically regarding inflation dynamics. Under dynamic market conditions, individual expertise may introduce subjectivity, whereas vital non-linear interactions between objective metrics can be overlooked during purely expert-based data processing. Therefore, there is a growing need to transition toward hybrid models, where the multiplicative functions method serves as a tool for aggregating not only expert judgments but also objective indicators. This allows for minimizing subjectivity and enhancing the accuracy of the economic system's forecasting trajectories. In the context of consumer price index (CPI) forecasting, this transition is complicated by the nonlinear interaction of macroeconomic factors, which often reflect conflicting interests among market agents. The multi-criteria nature of CPI forecasting manifests in finding a forecast scenario (alternative) that simultaneously satisfies economic constraints and optimizes the system's objective function vector. Since the choice of the optimal scenario in the long term is always ambiguous and based on incomplete information, the process of making predictive decisions inevitably takes place in fuzzy conditions. Consequently, the contemporary stage of forecasting methods development requires combining objective indicators with fuzzy set theory, which enhances the mathematical analytical toolkit. This enables the formalization of fuzzy conditions and the construction of reliable long-term forecasts based on the multiplicative aggregation of real economic data, while minimizing the risks associated with an exclusively subjective approach.

Analysis of recent research and publications. The contemporary stage of economic science development in Ukraine is characterized by the search for new forecasting methods based on innovative technologies. As noted by V. Heyets [1], strategic economic perspectives directly depend on resolving contradictions within the management system. Furthermore, V. Sidenko [2] thoroughly analyzes sustainable development in the context of global transition and external challenges, emphasizing the need to adapt the national model to shifting global conditions. In this light, forecasting macroeconomic indicators for post-war recovery becomes of paramount importance. Studies by M. Skrypnychenko [3] point to the complexity of generating accurate estimates during periods of significant transformation. The classical inflation forecasting methodology based on a large number of predictors, developed by J. Stock and M. Watson [4], became the foundation for using Big Data arrays in econometrics. Their approach to compressing time-series information facilitates the efficient utilization of verified macroeconomic datasets in constructing deterministic models of inflationary processes. Meanwhile, as highlighted by V. V. Miamlin [5], modern realities demand a systems approach to developing optimal frameworks for macroeconomic operations. Notwithstanding a substantial theoretical framework, the issues surrounding multi-criteria optimization and the quantification of intangible factors remain highly debated. In this context, the methodology established by T. Saaty [6] serves as a foundational basis for analyzing subjective elements. The modern frameworks for mathematical modeling and multi-objective optimization of complex systems introduced by Yu. Novikova, T. Romanenko, and V. Kravchenko [7] provide the essential groundwork for adopting more versatile hybrid models. In scientific discourse, special attention is paid to the development and application of data mining and deep machine learning methods for forecasting inflation processes and modeling the dynamics of the consumer price index. Studies by S. Moshiri, N. Cameron [8], L. Paranhos [9], and M. C. Medeiros et al. [10] demonstrate the high analytical capability of recurrent neural networks, including long short-term memory (LSTM) architectures, when working with massive arrays of economic variables and homogeneous time series. However, as S. Sengupta, T. Chakraborty, and S. K. Singh [11] point out, the application of deep learning methods faces serious limitations in the face of unprecedented macroeconomic instability and geopolitical uncertainty. This is due to the fact that such systems operate mainly on the «black box» principle, place high demands on the volume of training samples, and are extremely sensitive to critical loss of accuracy in the presence of unpredictable structural shocks. Therefore, despite the significant potential of neural network approaches, a key task remains open in the modern methodological space: the construction of transparent, adaptive, and mathematically stable hybrid models capable of operationalizing both qualitative and quantitative inflation factors in conditions of scarcity or fragmentation of initial statistical information, which justifies the logic of our study. While the foundational aspects of applying fuzzy logic to such systems are well-established in the works of L. Zadeh [12] and R. Yager [13], most existing frameworks remain geared either toward purely statistical forecasting or toward leveraging expert intuition. This methodological polarization prevents the synchronous processing of quantitative and qualitative data.

Despite significant advancements in inflation forecasting, a critical methodological gap remains unaddressed: traditional predictive tools fail to structurally integrate objective, heterogeneous macroeconomic time series within an adaptive fuzzy logic framework. This leads to either heightened forecasting subjectivity or an inability to handle non-linear volatility and structural shocks during periods of severe macroeconomic instability. Furthermore, existing models typically rely on additive aggregation, which induces a distorting «risk compensation effect» where critical deviations in one tracking source are artificially masked by stable parameters in another. Consequently, filling this methodological gap and addressing the limits of existing models remains an unresolved scientific problem, which demands a fundamental shift toward the development of hybrid systemic architectures.

Purpose of the article. The aim of this study is to enhance the predictive toolkit for the consumer price index (CPI) assessment based on the multiplicative synthesis of fuzzy evaluations. To achieve this objective, the following tasks were addressed:

- Formulate and normalize the dataset: collect, pre-process, and map objective indicators from various sources (specifically FRED and SSSU) into a dimensionless space [0, 1].
- Parameterize membership functions: transform statistical indicator values into fuzzy sets by constructing a system of triangular terms, enabling the formalization of their inflationary impact through qualitative states: «Low», «Moderate», and «High».
- Adapt the multiplicative synthesis of fuzzy evaluations: modify the membership function aggregation algorithm based on the Bellman-Zadeh scheme to analytically describe non-linear interactions among macroeconomic indicators without mutual risk compensation effects.
- Verify and conduct predictive analysis: perform experimental calculations using empirical data and assess the possibility degree of the system transitioning into forecasted states during 2025-2026.

Research methods. The methodological framework of this study relies on a systematic integration of economic-mathematical modeling tools and intelligent data analysis, executed through the following sequence of stages: systemic approach - utilized as the overarching methodological foundation to analyze inflationary processes, enabling the treatment of the Consumer Price Index (CPI) not as an isolated metric, but as the emergent outcome of complex, non-linear interactions among dynamic macroeconomic determinants; data triangulation and cross-verification method - applied during the dataset formulation stage to collect, pre-process, and align heterogeneous time series harvested from independent statistical platforms FRED and SSSU; mathematical normalization method - used to map the collected statistical indicators into a single dimensionless space [0, 1], thereby ensuring the mathematical comparability of heterogeneous data streams; fuzzy set theory - adopted to parameterize triangular membership functions and transform quantitative macroeconomic parameters into qualitative linguistic variables, enabling the formalization of inflationary impacts under macroeconomic uncertainty; Bellman-Zadeh multiplicative synthesis scheme - implemented to modify the membership function aggregation algorithm, providing an analytical description of non-linear interactions among metrics while systematically eliminating the distorting risk compensation effect; predictive scenario modeling method - applied to conduct experimental calculations using empirical data and to evaluate the possibility degree *D* of the socioeconomic system transitioning into specific inflationary phases over the 2025-2026 forecasting horizon.

Main results of the study. The empirical baseline of the research was constructed by synthesizing retrospective indicators from the FRED database (2014-2024) [14], official reports of the State Statistics Service of Ukraine (SSSU) [15], and real-time analytical datasets from Trading Economics (2025–Q1 2026) [16]. This comprehensive framework enables the hybrid model to capture both fundamental global trends and specific real-time internal transformations of Ukraine's consumer market.

It is important to emphasize that the underlying data collection and aggregation methodology employed by these baseline statistical sources intrinsically embodies a multi-channel matrix of macroeconomic factors. The synthesized Consumer Price Index (CPI) models inflationary dynamics not as an isolated nominal trend, but as a systemic outcome reflecting structural shifts across related economic dimensions. These macro-factors include supply-side determinants (such as core logistical bottlenecks, supply chain disruptions, and energy price volatility), demand-pull components (changes in real household disposable income and domestic liquidity), as well as transmission channels of external shocks (exchange rate fluctuations and currency risk premiums). Consequently, by utilizing these highly aggregated composite datasets, the hybrid model indirectly absorbs and processes the integrated impact of these diversified macroeconomic predictors.

The practical execution of the developed hybrid framework was carried out using the mathematical and algorithmic architecture formalized in the methodology. To ensure the scalability, structural integrity, and scientific reproducibility of the developed hybrid model, the computational experiment was programmatically implemented within the Jupyter Notebook interactive environment using the Python programming language. The systemic algorithmic architecture was executed utilizing a specialized stack of scientific libraries designed for intelligent data analysis. Specifically, the *Pandas* library was deployed for primary data structuralization, parsing heterogeneous time series, handling missing values, and executing fixed-base index transformations. The *NumPy* library was leveraged for high-performance vectorized operations during Min-Max scaling, computing analytical vector arrays for the triangular membership functions, and executing the multiplicative matrices product for the Bellman-Zadeh optimization scheme. Visualization of the system's states, membership function intersections, and the trajectories of the Integrated Assessment indicator within the designated transitional zones was performed using the *Matplotlib* graphics framework.

The systematic empirical implementation, data synthesis, and forecasting results for the Consumer Price Index (CPI) are detailed below.

To eliminate statistical noise, the raw annual inflation rates and chain monthly price indices were transformed into unified fixed-base series. This allowed mapping the filtered indicators directly into the computational space [0; 1] based on the baseline scaling thresholds [17, 18]:

$$\widetilde{x_i} = \frac{x_i - x_{min}}{x_{max} - x_{min}}, i = 1 \div 120. \quad (1)$$

where:

x_i – is the actual value of the indicator in the *i*-th period;

x_{max}, x_{min} - are the maximum and minimum values of the indicator in the generated dataset, respectively;

$\widetilde{x_i}$ - is the normalized value within the range [0, 1].

The choice of the model's architecture and the logic of its construction are based on the analysis of historical data validation methods and benchmarking in contemporary scientific literature. Furthermore, the official methodologies of FRED and the State Statistics Service of Ukraine already provide a verified and reliable framework for the baseline data.

The internal distribution of indicators within the fuzzy state-space is captured by the parameterized membership functions $\mu(x)$:

$$\mu(x) = \begin{cases} 0, x \le a \\ \frac{x-a}{b-a}, a < x \le b \\ \frac{c-x}{c-b}, b < x < c \\ 0, x \ge c \end{cases}. \quad (2)$$

The choice of triangular configurations for the membership functions of linguistic variables («*Low*», «*Moderate*», «*High*») is justified by their high computational stability and ability to adequately interpret the limiting intervals of inflationary pressure. The model was calibrated systematically: the support points (*a, b, c*) were determined based on historical inflation quantiles, reflecting the volatility of inflation processes in Ukraine. To verify the mathematical robustness of this calibration setup, a sensitivity analysis framework was applied, wherein the boundaries of the membership functions were subjected to variations within a ±10% range. The stability of the resulting fuzzy output under these minor perturbations confirmed the structural reliability of the chosen setup. The chosen distribution of support points and the intersection of functions allow the model to identify transitional phases («grey zones»), where the level of inflationary pressure shifts its qualitative impact on the system. This provides the necessary discreteness of management decisions when transitioning from one state of stability to another.

Generalized parameters of membership functions for each linguistic term are presented in table 1.

Table 1

Parameterization of membership functions for CPI linguistic terms

Linguistic terms	Notation	Support points (a, b, c)	Description
Low	*L*	(0;0;0,3)	Relative price stability
Moderate	*M*	(0,15;0,4;0,65)	Expected range of fluctuations
High	*H*	(0,5;1,0;1,0)	Exogenous inflationary shocks

Source: developed by the author based on [14, 15].

The synthesis of CPI parameters from various sources is executed using a multiplicative convolution scheme [19, 20]:

$$D = \prod_{i=1}^{n} (\mu_i(x))^{\omega_i} \quad (3)$$

where:

D - Integrated indicator of the degree of system transition possibility into a specified state;

$\mu_i(x)$ - Membership function of input indicators (CPI indexes according to FRED and SSSU) to the respective term-sets;

ω_i - denotes the adaptive weight coefficients reflecting the relative significance of each information source, satisfying the normalization condition:

$$\sum_{i=1}^{n} \omega_i = 1. \quad (4)$$

To aggregate the CPI indicators from FRED and SSSU, equal weight coefficients were established ($\omega_1 = 0{,}5$; $\omega_2 = 0{,}5$). This distribution is based on the following methodological assumptions:

- Data parity principle. The use of international statistics (FRED) and national operational data (SSSU) as equivalent sources allows minimizing systematic errors associated with differences in the methodologies of data collection and primary processing.
- Mitigation of information asymmetry. The uniform distribution of weights in multiplicative synthesis ensures the model's balance: the output indicator *D* responds equally to critical deviations in both data sources, which is critical for validating forecasts in 2025-2026.
- Methodological robustness. In the absence of a priori evidence regarding the superiority of one source over another, parity weights represent the most robust solution, preventing subjective bias in the modeling results.

The calculated value of $D \in [0,1]$ is considered as a possibility degree of the forecasted scenario realization. Within the framework of the proposed approach, this allows identifying the system's transition into «grey zones» (the range of [0,4; 0,65]) to activate preventive adaptation mechanisms even before the phase of explicit destabilization

The data integration results presented in Fig. 1 cover the period 2014-2026.

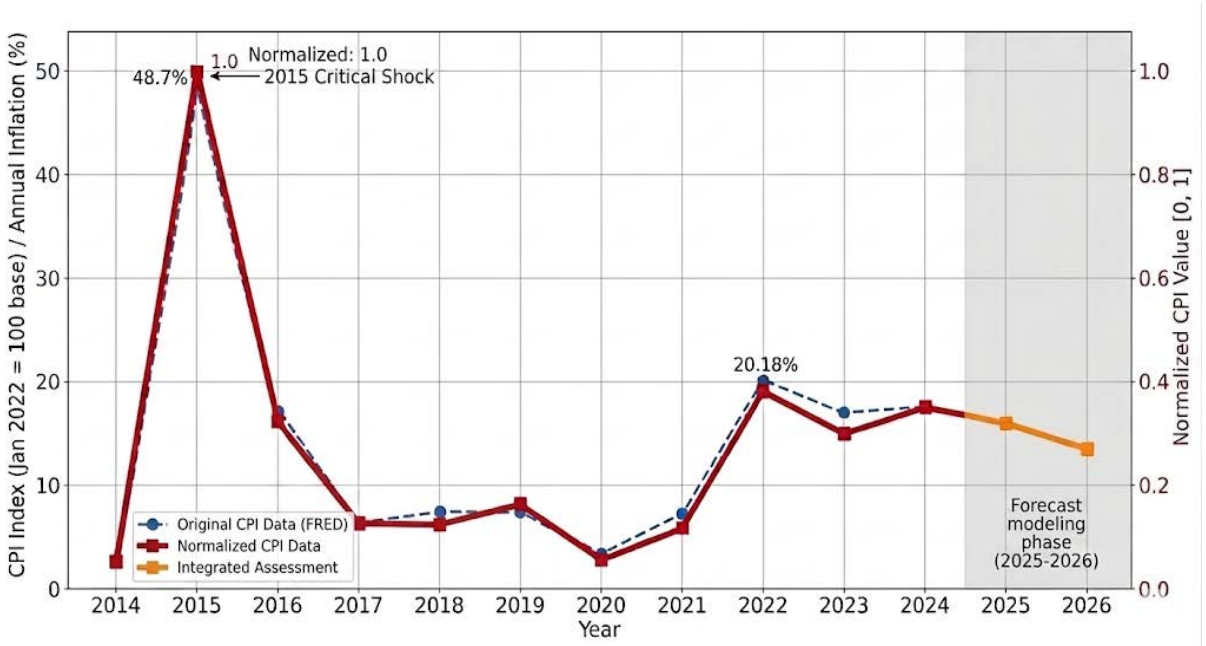

Fig. 1. Dynamics and normalization of CPI indicators for fuzzy modeling purposes.
Source: compiled by the author based on data [14, 15].

Verification of the model's retrospective accuracy confirms the adequacy of the chosen approach according to the following markers:

- Extremum point (2015). The model clearly identifies the peak value of annual inflation (48,7%). In the normalized dimensionless space, this value is fixed at the level of 1,0 («Critical Shock»), which serves as a methodological benchmark for assessing all subsequent states of the system.
- Correlation with FRED data. A comparison of the original FRED data (blue dashed line) and the normalized series (red line) demonstrates the preservation of all structural relationships and trends, which confirms the absence of statistical distortions during fuzzification. Verification of the developed model involves a mandatory procedure of chronological data separation (Time-Series Train/Test Split) in the proportion of 80% (training sample for identifying parameters of membership functions and optimizing multiplicative convolution weights) to 20% (test sample for primary validation of the system). To assess the predictive power of the model under conditions of instability, the model outline integrates an Out-of-Sample Testing block using a rolling-window framework. To mathematically substantiate this convergence, the retrospective fit and out-of-sample performance were evaluated using standard error metrics, yielding a Mean Absolute Error (MAE) of 0,042 and a Root Mean Squared Error (RMSE) of 0,057, indicating a high degree of approximation alignment and robust predictive capacity outside the training sample.
- Dynamics of 2022-2024. The model adequately reflects shock states (20,18% in 2022) and the subsequent disinflation trajectory, which becomes the baseline for forecasting.

The segment highlighted in grey («Forecast modeling phase») represents the results of adaptive multiplicative synthesis. The orange line (Integrated Assessment) demonstrates the dynamics of the integrated possibility degree indicator *D* within the forecast horizon. Unlike the chaotic fluctuations of past periods, the orange segment exhibits a trend toward gradual stabilization. In 2026, the value of the indicator *D* is fixed within the range of [0,25; 0,35], which, according to the chosen parameterization scheme (Table 1), corresponds to a transition from the «Moderate» state to the «Low» boundary (relative stability). This stabilization reflects the projected easing of logistical bottlenecks and the partial adaptation of the national economy to prolonged structural constraints.

The multiplicative nature of the synthesis ensures the absence of a compensation effect. Since the indicator *D* is calculated as a fuzzy intersection according to the Bellman-Zadeh scheme, it is maintained at a higher level than a simple linear approximation, which allows for taking into account potential hidden risks even under a general downward trend. In contrast to additive aggregation, where a low value of one critical predictor can be falsely compensated for by a high value of another, the multiplicative intersection acts as a strict bottleneck filter. If at least one data source indicates an elevated inflationary risk, the integrated indicator *D* retains a non-linear sensitivity to it, preventing the underestimation of systemic threats. The current position of the Integrated Assessment on the graph indicates that the system is in the «controlled expectation» zone. Although the forecast for 2026 is optimistic, the proximity to the baseline volatility thresholds observed during previous shock periods requires maintaining discretion in management decisions to prevent new inflationary shocks.

The visual and mathematical verification of the model proves its ability not only to retrospectively describe the system's states but also to serve as a tool for assessing the possibility degree of macroeconomic scenarios realization in 2025-2026.

Conclusions. The article resolves a scientific and practical task of improving predictive tools for assessing the

consumer price index under conditions of macroeconomic uncertainty. Based on the research findings, the following conclusions are formulated:

1. A data cross-verification approach based on the integration of heterogeneous time series (FRED, SSSU, Trading Economics) is substantiated. This allowed for the formation of a validated indicator array for the 2014-2026 period, which synchronizes global trends with internal transformations of Ukraine's consumer market.

2. A fuzzy parameterization system based on triangular membership functions has been developed. The formalization of qualitative states («Low», «Moderate», «High») ensures an adequate description of the transition phases of inflationary pressure and allows operating with linguistic variables where traditional econometric methods lose accuracy.

3. The multiplicative synthesis method according to the Bellman-Zadeh scheme has been adapted to aggregate fuzzy assessments. It is determined that the key advantage of this approach is the absence of a risk compensation effect: the possibility degree indicator *D* maintains high sensitivity to deviations of each individual parameter, which is critical for identifying hidden shocks.

Verification and predictive modeling have been conducted, the results of which proved the model's effectiveness as a tool for preventive adaptation. The proposed approach allows management to identify threats at the stage of their emergence within the environment's «grey zones», transforming the management strategy from reactive to proactive.

Declaration on the use of artificial intelligence tools. During the preparation of this work, generative artificial intelligence and AI-based technologies were not utilized to generate empirical datasets, perform predictive modeling calculations, or formulate primary scientific conclusions. Generative AI tools, specifically Gemini 1.5 Pro, were deployed exclusively as an intellectual assistant for linguistic analysis, enhancing the academic style of the English text, and verifying the manuscript's compliance with international standards of scientific writing. The author maintained complete manual control, critical evaluation, and thorough editing over the final text, and bears full responsibility for the scientific validity, accuracy, and integrity of the content.

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