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Modeling the Technological Labor Market under Markov Switching, Phase Aggregation, and Levy Approximation

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Abstract

We construct and study a continuous evolutionary model describing the conflict interaction between automation and the labor market in strategic IT sectors. The system dynamics are based on the Lotka-Volterra framework, enhanced by Markov switching and Levy-type stochastic jumps. This allows for describing the impact of rare but critical events that abruptly change employment levels. By applying phase merging methods, we derive a reduced model that preserves key asymptotic behavior. The approach serves as a tool for analyzing market resilience and strategic risks under global uncertainty.

KEY WORDS: *phase aggregation; reducible-invertible operators; singular problem perturbation; Levy approximation; technology labor market.*

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1. Introduction

The rapid evolution of artificial intelligence (AI) and generative models has initiated a profound transformation of the global labor market, positioning AI as a defining general-purpose technology of the 21st century [5, 10]. Unlike previous waves of automation that primarily targeted routine manual and cognitive tasks [8, 9], modern AI systems demonstrate an unprecedented capacity to augment or automate high-level cognitive functions across strategic sectors [1, 4, 7]. From the perspective of national and economic security, the stability of the labor market in critical infrastructure and the IT sector is no longer just an economic metric but a vital component of a state's resilience against technological shocks and hybrid threats [17].

Recent empirical evidence suggests that the impact of AI is highly heterogeneous. While software development has seen significant productivity gains – exemplified by tools like GitHub Copilot [3] – the broader macroeconomic effects remain complex and often elude detection at the initial stages of implementation [6]. Traditionally, the interaction between technology and labor has been modeled as a «race» [2, 9]; however, the stochastic nature of AI breakthroughs and the non-linear innovation diffusion rates [11], necessitate more sophisticated mathematical frameworks. In contemporary geopolitical situations, the ability to predict and mitigate «innovation shocks» is essential for maintaining strategic advantage and social stability [17].

A common strategy used to study such interactions is the application of predator-prey frameworks, rooted in the classical works of Volterra [12]. Nevertheless, deterministic models often fail to account for sudden regime shifts or critical «black swan» events (Lévy-type shocks). To address this, recent theoretical developments have emphasized the importance of Markov switching [24, 25] and random perturbations [23] in representing the volatility of complex systems [15, 20-23].

The analytical investigation of such high-dimensional stochastic systems is frequently complicated by significant computational and structural complexity. To overcome this, we employ the method of phase merging of the system's space [13, 14, 32]. Based on the theory of stochastic systems in merging phase spaces and the application of limit theorems for switching processes [18, 19], we utilize the formalism of redundant-invertible operators to handle singular perturbations.

This approach, further extended to double merging, averaging principles, and diffusion approximation conditions [27-33], allows for the derivation of reduced asymptotic models [15, 16]. Such models preserve the essential qualitative behavior of the labor market while significantly simplifying computational complexity.

The main contribution of this work is the construction of a continuous evolutionary model that integrates Markov switching and Lévy-type stochastic jumps to describe the impact of critical AI milestones on employment levels in strategic sectors. By employing phase aggregation, we provide a robust mathematical tool for analyzing market resilience and strategic risks. This is particularly relevant for ensuring national security in an era where technological dominance and labor market stability are inextricably linked.

2. The «classical» labour market model

We consider a well-known "toy" predator–prey type model that describes the dynamic interaction between human employment and the implementation of automated systems [13]:

$$\begin{cases} \dfrac{dN(t)}{dt} = aN(t) - bN(t)A(t) - cN^2(t) \\ \dfrac{dA(t)}{dt} = -dA(t) + eN(t)A(t), \quad t > 0 \end{cases}, \tag{1}$$

where

$N(t)$ – the number of employees in the IT sector at time t (i.e., individuals currently working in the industry);

$A(t)$ – the level of automation at time t (the extent to which AI and automated technologies are implemented in IT). To ensure dimensional consistency, $A(t)$ is interpreted as the equivalent number of IT specialists at time t that would be required to perform the same work without automation.;

a – the natural growth coefficient of IT employment, indicating rising demand for specialists;

b – the negative impact of automation, where higher levels of automation reduce the need for IT specialists;

cN^2 – the effect of competition within the IT workforce: a larger number of specialists leads to stronger competition for jobs;

dA – the natural decline of automation caused by technological obsolescence and the need for maintenance and adaptation;

eN – represents the growth of automation driven by collaboration between IT professionals and technology through the development and implementation of AI.

The proposed system represents a deterministic model describing the interaction between the number of IT employees and the level of automation in the industry. However, such a deterministic framework cannot fully capture the real behavior of the labor market under uncertainty, since it does not account for unexpected shocks or abrupt changes that may increase or decrease employment levels or automation intensity. Therefore, to better reflect the stochastic nature of technological and labor-market dynamics, it is necessary to extend the model using aggregation techniques and stochastic perturbations.

3. Merging of phase space under Levy approximation conditions

We consider a stochastic evolutionary system operating in an ergodic Markov environment:

$$du^\varepsilon(t) = C\big(u^\varepsilon(t), x(t/\varepsilon^3)\big)dt + d\eta^\varepsilon(t),\ u^\varepsilon(t) \in \mathbb{R}, \tag{2}$$

where$x^\varepsilon(t), t \geq 0$ is a Markov process defined on a standard phase space $(E, \mathcal{E})$ with a splitting:

$$E = \bigcup_{k=1}^{N} E_k\, , E_k \cap E_j = \emptyset, k \neq j,$$

under a small parameter scaling $\varepsilon \to 0, \varepsilon > 0$ and is defined by a singularly perturbed transition kernel:

$$\boldsymbol{Q}^\varepsilon(x, B, t) = P^\varepsilon(x, B)[1 - exp - q(x)t], x \in E, B \in \varepsilon, t \geq 0.$$

Let us consider the following assumptions:

1. The kernel describing the transition probabilities of the embedded Markov chain $x_n^\varepsilon, n \geq 0$ is defined as follows

$$P^\varepsilon(x, B) = P(x, B) + \varepsilon P_1(x, B).$$

The stochastic kernel $P(x, B)$ on the split phase space is defined as

$$P(x, E_k) = 1_k(x) = \begin{cases} 1, x \in E_k \\ 0, x \notin E_k. \end{cases}$$

The stochastic kernel $P(x,B)$ defines the accompanying Markov chain $x_n, n \geq 0$ on the classes $E_k, 1 \leq k \leq N$. Furthermore, the perturbation kernel $P_1(x,B)$ satisfies the condition $P_1(x,B) = 0$, which is a direct consequence of the equality $P^\varepsilon(x,E) = P(x,E_k) = 1$.

2. Associated Markov process $x^0(t), t \geq 0$, is defined by the operator

$$Q\varphi(x) = q(x) \int_E P(x,dy)[\varphi(y) - \varphi(x)],$$

is uniformly ergodic within each of the classes $E_k, 1 \leq k \leq N$, with the stationary distribution $\pi_k(dx), 1 \leq k \leq N$ satisfied the relation:

$$\pi_k(dx)q(x) = q_k\rho_k(dx), q_k := \int_{E_k} \pi_k\,(dx)q(x).$$

3. Average probability of exit

$$\widehat{p_k} := \int_{E_k} \rho_k\, P_1(x, E/E_k) > 0, 1 \leq k \leq N.$$

Thus, the perturbation kernel $P_1(x,B)$ determines the transition probabilities between the classes $E_k, 1 \leq k \leq N$, therefore, the equality

$$P^\varepsilon(x,B) = P(x,B) + \varepsilon P_1(x,B)$$

implies that the embedded Markov chain $x_n^\varepsilon, n \geq 0$ spends a long time within each class E_k and undergoes transitions between classes with small probabilities $\varepsilon P_1(x, E/E_k)$.

Under conditions ME1–ME3, the weak convergence of random processes holds [5]:

$$\nu\big(x^{\varepsilon}(t)\big) \Rightarrow \hat{x}(t)\,, \varepsilon \to 0,$$

where the phase space merging function is defined as $\nu(x) = k \in \hat{E} = 1, \dots, N, x \in E_k, 1 \leq k \leq N$.

The limit Markov process $\hat{x}(t), t \geq 0$, defined on the merged phase space $\hat{E} = \{1, \dots, N\}$ is given by the generator matrix:

$$\hat{Q}_1 = (\hat{q}_{kr}, 1 \leq k, r \leq N),$$

whose entries are given by the following relations:

$$\hat{q}_{kr} = \hat{q}_k \hat{p}_{kr}, k \neq r, \hat{q}_k = q_k \hat{p}_k, 1 \leq k \leq N,$$

here, the parameters of the merged system are determined via the characteristics of the initial process as follows:

$$\hat{p}_{kr} = \frac{p_{kr}}{\hat{p}_k}, \qquad p_{kr} = \int_{E_k} \rho_k(dx) P_1(x, E_r)\,, 1 \leq k, r \leq N, k \neq r,$$

$$\hat{p}_k = -\int_{E_k} \rho_k(dx) P_1(x, E_k).$$

where $\rho_k(dx)$ – is the stationary distribution of the embedded Markov chain within the class E_k; $P_1(x, E_r)$ – the transition probabilities from a state x of class E_k to class E_r.

4. The merged Markov process $\hat{x}(t), t \geq 0$ is an ergodic process with the stationary distribution $\hat{\pi} = \big(\pi_k, k \in \hat{E}\big)$.

Thus, the operator $\boldsymbol{Q}^\varepsilon$ can be represented as a perturbed operator:

$$\boldsymbol{Q}^\varepsilon = \boldsymbol{Q} + \boldsymbol{\varepsilon Q_1}, \boldsymbol{Q_1}(\boldsymbol{x}) = \boldsymbol{q}(\boldsymbol{x}) \int_{\boldsymbol{E}} P_1(x,dy)\, \varphi(\boldsymbol{y}),$$

where $\boldsymbol{Q}^\varepsilon = \boldsymbol{Q} + \boldsymbol{\varepsilon Q_1}$

$$\boldsymbol{Q}(\boldsymbol{x}) = \boldsymbol{q}(\boldsymbol{x}) \int_{\boldsymbol{E}} P(x,dy)\, [\varphi(\boldsymbol{y}) - \varphi(\boldsymbol{x})], \boldsymbol{Q_1}(\boldsymbol{x}) = \boldsymbol{q_1}(\boldsymbol{x}) \int_{\boldsymbol{E}} P_1(x,dy)\, \varphi(\boldsymbol{y}).$$

Let Π be the projector to zero-subspace of a reducible-invertible operator $\boldsymbol{Q}$. Its effect on the test functions is defined as follows:

$$\boldsymbol{\Pi}\varphi(x) = \sum_{k=1}^{N} \hat{\varphi}_k 1_k(x), \hat{\varphi}_k := \int_{E_k} \pi_k(dx)\varphi(dx).$$

Reducible operator $\hat{Q}_1$ can be determined by relation $\hat{Q}_1\Pi = \Pi Q_1 \Pi$.

Let $\hat{\Pi}$ be the projector to zero-subspace of a reducible-invertible operator $\hat{Q}_1$:

$$\hat{\Pi}\hat{\varphi} := q(x) \sum_{k \in E} \hat{\pi}_k \hat{\varphi}_k.$$

Potential matrix $\hat{R}_0 = \left[\hat{R}_{kj}^0; 1 \leq k, l \leq N\right]$ can be determined by relation

$$\hat{Q}_1 \hat{R}_0 = \hat{R}_0 \hat{Q}_1 = \hat{\Pi} - E.$$

In our study, the drift coefficient C of the stochastic system (2) has a Lotka–Volterra-type structure (1):

$$C\big(u^\varepsilon(t), x(t/\varepsilon^3)\big) = \begin{pmatrix} a - cN & -bN \\ eA & -d \end{pmatrix} \times \begin{pmatrix} N \\ A \end{pmatrix},$$

where $u^\varepsilon(t) = \big(N(t), A(t)\big)$, The phase space is defined as $E = \mathcal{L} \times A$, where $\mathcal{L} = l_1, l_2, l_3, l_4$, $A = \{a_1, a_2, a_3, a_4\}$.The elements of $l_i \in \mathcal{L}$ are interpreted as the qualification levels of employees, namely Trainee, Junior, Middle, and Senior; while $a_i \in A$ – represent the automation modes: Manual, Human+Automation (human-centric), Automation+Human (automation-centric), and Fully Automated. Thus, the state of the environment is represented as $x = (l_i, a_i) \in E$.

Since the transitions between automation modes occur faster than the transitions of employees between qualification levels, we split the phase space into the following classes:

$E = \bigcup_{k=1}^{4} E_k\,, E_k \cap E_j = \emptyset, k \neq j,$

where $E_k = l_k \times A, k = 1,2,3,4$. Accordingly, the merged phase space is defined as $\hat{E} = 1,2,3,4$, where the index k corresponds to the class E_k. The fast generator matrix $\boldsymbol{Q}$ has the following form:

$$\boldsymbol{Q} = \begin{pmatrix} -g_1 & g_1 & 0 & 0 \\ r_1 & -(r_1 + g_2) & g_2 & 0 \\ 0 & r_2 & -(r_2 + g_3) & g_3 \\ 0 & 0 & r_3 & -r_3 \end{pmatrix}$$

where g_i – the automation intensity of a task (fast forward transition), r_i – is the intensity of returning to manual labor (e.g., due to code errors or technological obsolescence).

In turn, the slow generator matrix Q_1 has the following form:

$$Q_1 = \begin{pmatrix} -(\lambda_1 + \mu_1) & \lambda_1 & 0 & 0 \\ \mu_1 & -(\mu_1 + \lambda_2 + \mu_2) & \lambda_2 & 0 \\ 0 & \mu_2 & -(\mu_2 + \lambda_3 + \mu_3) & \lambda_3 \\ 0 & 0 & \mu_3 & -\mu_3 \end{pmatrix}$$

where $\lambda_1, \lambda_2, \lambda_3$ – the intensities of skill upgrading (promotion rates), μ_1, μ_2, μ_3 – represents the intensities of resignation or demotion (employee turnover).

The full generator of the system Q^εacts on a phase space E of dimension 16 and possesses a block structure. The main diagonal blocks contain elements of the fast generator $\boldsymbol{Q}$ (automation), while the off-diagonal blocks are determined by the matrix Q_1 (qualification) multiplied by a small parameter ε.

The stationary distribution $\pi = (\pi_1, \pi_2, \pi_3, \pi_4)$ of the fast operator is determined by a system of equations $\pi\boldsymbol{Q} = 0$, subject to the normalization condition $\sum_{i=1}^{4} \pi_i = 1$. The system takes the following form:

$$\begin{cases} -g_1\pi_1 + r_1\pi_2 = 0, \\ g_1\pi_1 - (r_1 + g_2)\pi_2 + r_2\pi_3 = 0 \\ g_2\pi_2 - (r_2 + g_3)\pi_3 + r_3\pi_4 = 0, \\ g_3\pi_3 - r_3\pi_4 = 0 \end{cases}$$

From this, we obtain that $\pi_1 = \left[1 + \frac{g_1}{r_1} + \frac{g_1 g_2}{r_1 r_2} + \frac{g_1 g_2 g_3}{r_1 r_2 r_3}\right]^{-1}$, and accordingly, we then determine $\pi_2 = \frac{g_1}{r_1}\pi_1, \pi_3 = \frac{g_1 g_2}{r_1 r_2}\pi_1, \pi_4 = \frac{g_1 g_2 g_3}{r_1 r_2 r_3}\pi_1$.

The aggregated operator $\hat{Q}$ which describes the evolution of the merged process $\hat{x}(t)$ in the qualification phase space $\hat{E} = \{T, J, M, S\}$, is determined by the following relation $\hat{Q}_1\boldsymbol{\Pi} = \boldsymbol{\Pi} Q_1 \boldsymbol{\Pi}$ and has the form:

$$\widehat{Q_1} = \begin{pmatrix} -\lambda_1 & \lambda_1 & 0 & 0 \\ \mu_1 & -(\lambda_2 + \mu_1) & \lambda_2 & 0 \\ 0 & \mu_2 & -(\lambda_3 + \mu_2) & \lambda_3 \\ 0 & 0 & \mu_3 & -\mu_3 \end{pmatrix}$$

The Impulse Perturbation Process (IPP) $\eta^\varepsilon(t), t \geq 0$ [14-15], in the Lévy approximation scheme is given by the relation:

$$\eta^{\varepsilon}(t) = \int_0^t \eta^{\varepsilon}\big(ds, x^{\varepsilon}(s/\varepsilon^3)\big) \tag{3}$$

where $\eta^{\varepsilon}(t,x), t \geq 0, x \in X$ is set of processes with independent increments is defined by the generators:

$$\boldsymbol{\Gamma}^{\varepsilon}(x)\varphi(w) = \varepsilon^{-2}\int_R \big(\varphi(w+v) - \varphi(w)\big)\,\Gamma^{\varepsilon}(dv,x), x \in X \tag{4}$$

and satisfy the conditions of the Lévy approximation

L1: Approximation of averages

$$\int_R v\Gamma^{\varepsilon}(dv,x) = \varepsilon a_1(x) + \varepsilon^2\big(a_2(x) + \theta_a(x)\big), \theta_a(x) \to 0, \varepsilon \to 0,$$

and

$$\int_R v^2\Gamma^{\varepsilon}(dv,x) = \varepsilon^2\big(b(x) + \theta_b(x)\big), \theta_b(x) \to 0, \varepsilon \to 0.$$

L2: Condition on the distribution function

$$\int_R g(v)\Gamma^{\varepsilon}(dv,x) = \varepsilon^2\Gamma_g(x) + \theta_g(x)), \theta_g(x) \to 0, \varepsilon \to 0$$

for each $g(v) \in C_3(\mathbb{R})$. Here, the measure $\Gamma_g(x)$ is bounded for all $g(v) \in C_3(\mathbb{R})$ and is determined by the relation:

$$\Gamma_g(x) = \int_R g(v)\Gamma_0(dv,x)\,, g(v) \in C_3(\mathbb{R})$$

where $C_3(\mathbb{R})$ is a class of functions that define the measure and contains bounded real-valued functions such that as $g(v)/|v|^2 \to 0, v \to 0$.

L3: Uniform quadratic integrability

$$\lim_{c\to\infty} \sup_{x\in X} \int_{|v|>c} v^2\Gamma_0(dv,x)$$

Let us denote:

$$\Gamma_1(x)\varphi(w) = a(x)\varphi'(w)$$

Assume that the balance condition holds:

$$\hat{\Pi}\hat{\Gamma}_1 = 0, \tag{5}$$

where $\hat{\Gamma}_1\hat{\varphi}(w) = \mathbf{\Pi}\Gamma_1(x)\varphi(w)$.

We investigate the asymptotic properties of the perturbation process.

Theorem 1. If the balance condition (5) and the Lévy approximation conditions L1–L3 are satisfied, then the weak convergence holds:

$$\eta^{\varepsilon}(t) \to \eta^0(t), \varepsilon \to 0$$

The limit process $\eta^0(t)$ is defined by the generator

$\hat{\hat{\Gamma}}\varphi(w) = \hat{\hat{a}}_2\varphi'(w) + \frac{1}{2}\hat{\hat{\sigma}}^2\varphi''(w) + \int_R[\varphi(w+v) - \varphi(v)]\hat{\hat{\Gamma}}_0(dv),$

where

$$\hat{\hat{a}}_2 = \sum_{k\,\in\,E}\hat{\pi}_k\int_{E_k}\pi_k\,(dx)\big(a_2(x) - a_0(x)\big),$$

$$\hat{\hat{\sigma}}^2 = \sum_{k\,\in\,E}\hat{\pi}_k\int_{E_k}\pi\,(dx)\big(b(x) - b_0(x)\big) + 2\sum_{k\,\in\,E}\hat{\pi}_k\int_{E_k}\pi\,(dx)a_1(x)R_0a_1(x),$$

$$\hat{\hat{a}}_0(x) = \sum_{k\,\in\,E}\hat{\pi}_k\int_{E_k} v\Gamma_0(dv,x),$$

$$\hat{\hat{b}}_0(x) = \sum_{k\,\in\,E}\hat{\pi}_k\int_{E_k} v^2\Gamma_0(dv,x),$$

$$\hat{\hat{\Gamma}}_0(v) = \sum_{k \in E} \hat{\pi}_k \int_{E_k} \pi\,(dx) \Gamma_0(v, x).$$

Thus, in the limit, we have obtained a Lévy process consisting of three components: a deterministic drift, a diffusion component, and a Poisson jump part.

Theorem 2. Under the balance condition and the Lévy approximation conditions L1–L3, the weak convergence in the sense of the convergence of generators holds:

$$\left(u^{\varepsilon}(t), \eta^{\varepsilon}(t)\right) \to \left(\hat{\hat{u}}(t), \eta^{0}(t)\right), \varepsilon \to 0.$$

The limit process $\left(\hat{\hat{u}}(t), \eta^{0}(t)\right)$ is defined by the generator:

$$\boldsymbol{L}\varphi(u, w) = \hat{\hat{C}}(u)\varphi'_{u}(u, w) + \hat{\hat{\Gamma}}_1^{u}\varphi(u,\cdot) + \hat{\hat{\Gamma}}_2^{w}\varphi(\cdot, w)$$

where

$$\hat{\hat{C}}(u) = \mathbf{\Pi} C(x) = \int_X \pi(dx) C(u, x)$$

The generators $\hat{\hat{\Gamma}}_1^{u}$ and $\hat{\hat{\Gamma}}_2^{w}$ share the same structure but act with respect to different values. The averaged function takes the form:

$$\hat{C}(u) = \int_X \pi(dx) C(u, x)$$

4. Numerical Simulations and Scenario Analysis

To illustrate the behaviour of the proposed labour market model, we consider several simulation scenarios with synthetic parameters.

For the baseline scenario the parameters of the local drift are specified for each automation regime as $a_j = (0.60, 0.57, 0.54, 0.50), b_j = (0.010, 0.018, 0.028, 0.040), c_j = (1.0 \cdot 10^{-4}, 1.0 \cdot 10^{-4}, 1.1 \cdot 10^{-4}, 1.2 \cdot 10^{-4}), d_j = (0.40, 0.46, 0.53, 0.60), d_j = (0.40, 0.46, 0.53, 0.60), e_j = (0.010, 0.015, 0.020, 0.026)$. Each value corresponds to one of the four automation modes (Manual, H+A, A+H, Fully Automated) and represents the local interaction between labour and automation in that regime. The effective coefficients of the classical aggregated model are then obtained by averaging these state dependent parameters with respect to the stationary distribution of the fast automation process. Diffusion intensities $\sigma_N = 0.005, \sigma_A = 0.005$ representing small continuous fluctuations in labour demand and automation capacity. Jump intensities $\lambda_N = 0.01, \lambda_A = 0.02$ reflecting higher volatility in automation dynamics. The parameters of the slow generator matrix Q_1 includes promotion rate $\lambda_1 = 0.12, \lambda_2 = 0.13, \lambda_3 = 0.10$ and downward transitions $\mu_1 = 0.10, \mu_2 = 0.08, \mu_3 = 0.06$ representing gradual career mobility and possible labour market restructuring. The fast generator matrix $\boldsymbol{Q}$ is defined by automation adoption rates $g_1 = 0.55, g_2 = 0.45, g_3 = 0.30$ and rollback rates $r_1 = 0.20, r_2 = 0.18, r_3 = 0.15$, allowing progressive automation with occasional returns to human intervention.

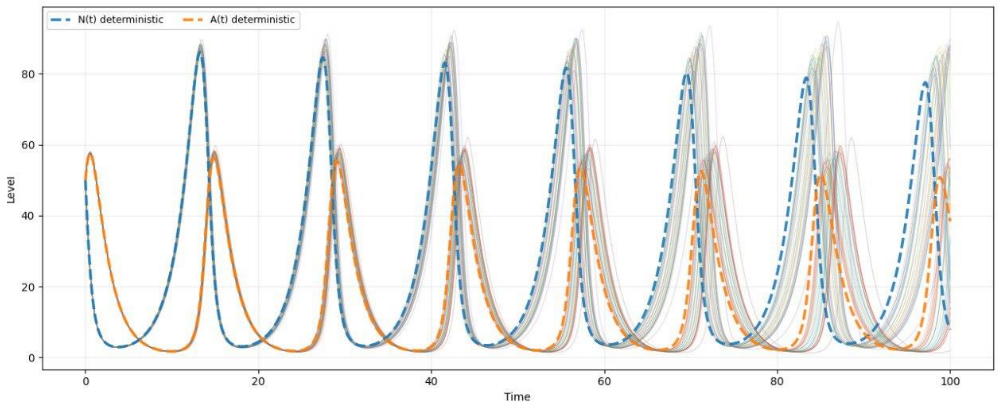

Fig. 1. Baseline scenario: deterministic vs stochastic dynamics of $N(t)$ and $A(t)$

The figure 1 illustrates the interaction between workforce $N(t)$ and automation level $A(t)$ under the baseline parameter configuration. Dashed curves denote the deterministic solution, while thin coloured lines represent stochastic Lévy trajectories. The deterministic dynamics display cyclical behaviour reflecting feedback between labour supply and technological development. Random perturbations cause variability in the cycles, representing technological shocks such as the introduction of new AI tools or temporary technological rollback. Nevertheless, the stochastic trajectories remain close to the deterministic path, indicating structural stability of the system. At the initial moment the company employs $N(0) = 50$

workers distributed across qualification levels according to the vector $P(0) = (0.30, 0.20, 0.32, 0.18)$, which corresponds to 30% trainees, 20% junior specialists, 32% middle-level employees, and 18% senior specialists. Figure 2 shows the evolution of this workforce structure obtained from the aggregated model with parameters averaged over the stationary distribution of the fast automation process, presented over a ten-year horizon.

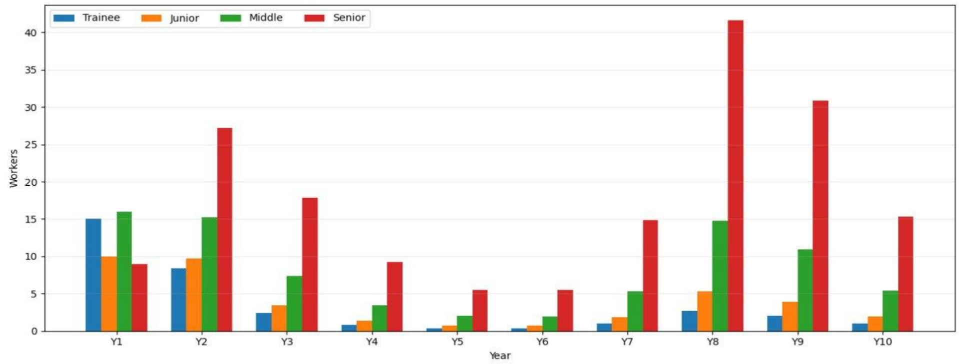

Fig. 2. Baseline scenario: workforce structure in the aggregated system

The results indicate that the largest share of employees gradually concentrates in the middle and senior categories, reflecting the dominance of upward qualification transitions in the generator Q_1. At the initial moment the total automation level is $A(0) = 50$. In the aggregated model, the task structure is determined by the stationary distribution of the fast automation process. Figure 3 illustrates the evolution of the task structure over a ten-year horizon, where the effective parameters are averaged with respect to this invariant distribution.

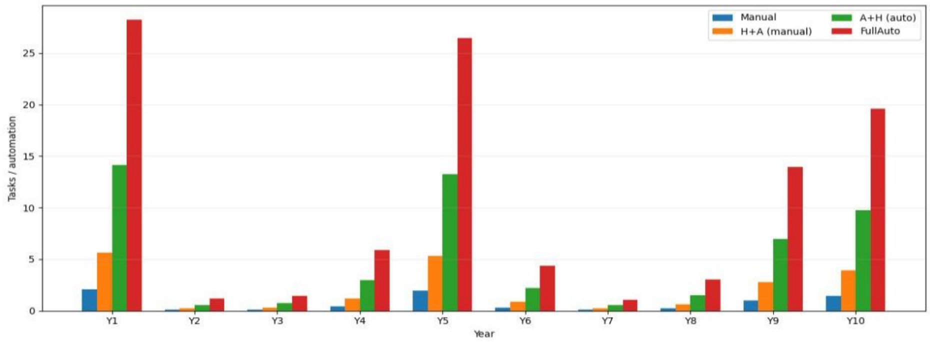

Fig. 3. Baseline scenario: task automation structure in the aggregated system

The results indicate a gradual shift toward automation-intensive regimes, with a growing share of A+H and fully automated tasks. This behaviour reflects the dominance of forward automation transitions in the generator $\boldsymbol{Q}$, which drives the system toward more technologically intensive production modes. For the scenario accelerated automation environment the parameters of the local drift are the same. The Lévy diffusion coefficients are $\sigma_N = 0.005, \sigma_A = 0.006$ with jump intensities $\lambda_N = 0.01, \lambda_A = 0.04$, indicating higher volatility in automation dynamics.

The parameters of the slow generator matrix Q_1 remain the same. The parameters of the fast generator matrix $\mathbf{Q}$ are modified by increasing the forward transition rates and reducing the rollback rates $\mathrm{g}_1 = 0.65, \mathrm{g}_2 = 0.52, \mathrm{g}_3 = 0.38, \mathrm{r}_1 = 0.15, \mathrm{r}_2 = 0.12, \mathrm{r}_3 = 0.10$, allowing tasks to move more rapidly toward higher levels of automation while reducing the probability of returning to less automated states.

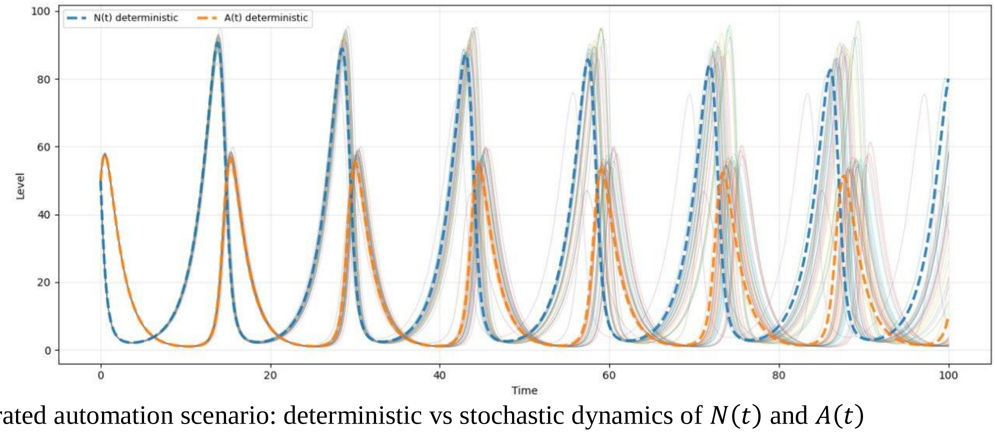

Fig. 4. Accelerated automation scenario: deterministic vs stochastic dynamics of $N(t)$ and $A(t)$

Compared to the baseline scenario, this configuration exhibits higher variability due to stronger technological shocks. Nevertheless, the cyclical interaction between labour and automation remains stable, with stochastic trajectories fluctuating around the deterministic dynamics. At the initial moment the total number of employees and their distribution across qualification levels remain the same as in the baseline scenario. Figure 5 shows the evolution of this workforce structure obtained from the aggregated system over a shortened horizon of ten years.

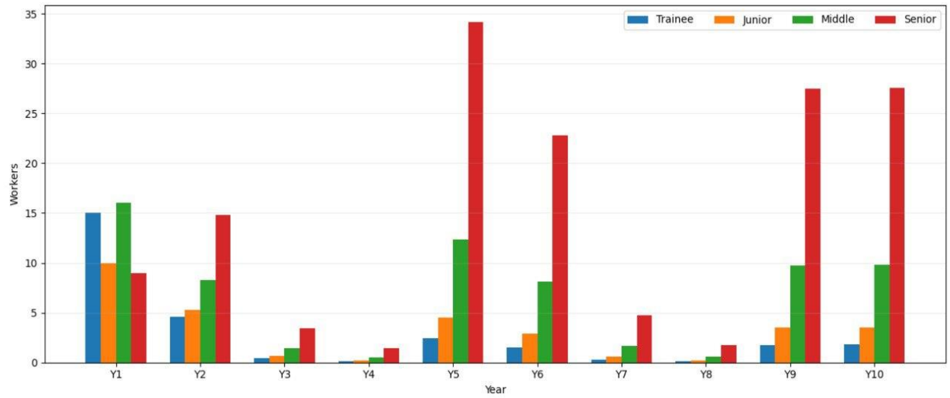

Fig. 5. Accelerated automation scenario: workforce structure in the aggregated system

Compared with the baseline scenario, the model demonstrates a stronger concentration of employees in the senior category, accompanied by a faster decline in lower qualification levels. This indicates a higher intensity of upward qualification transitions within the workforce structure. At the initial moment the total automation level with the task structure is determined by the stationary distribution of the fast automation process. Figure 6 illustrates the evolution of the task structure obtained from the aggregated system over a ten-year horizon.

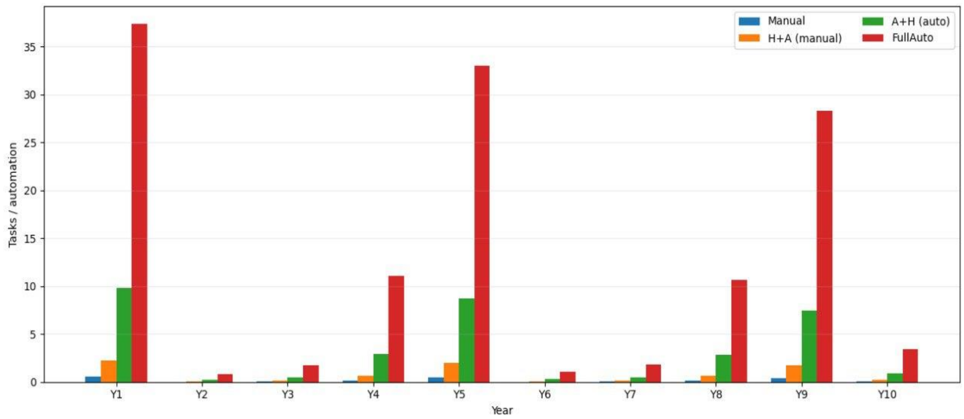

Fig. 6. Accelerated automation scenario: task automation structure in the aggregated system

Compared with the baseline scenario, the transition toward highly and fully automated tasks occurs more rapidly. This indicates a stronger dominance of forward automation transitions in the generator $\boldsymbol{Q}$, leading to faster displacement of manual and partially assisted tasks.

For the scenario rollback manual, the parameters of the local drift are the same as for the previous scenarios, while the jump intensities of the automation process are reduced $\lambda_A = 0.015$, indicating less frequent technological shocks. The parameters of the slow generator matrix Q_1 remain the same. In contrast, the fast generator matrix $\boldsymbol{Q}$ is adjusted by decreasing the forward transition rates and increasing rollback rates $g_1 = 0.30, g_2 = 0.22, g_3 = 0.15, r_1 = 0.10, r_2 = 0.08, r_3 = 0.06$, allowing tasks to move back toward lower automation levels.

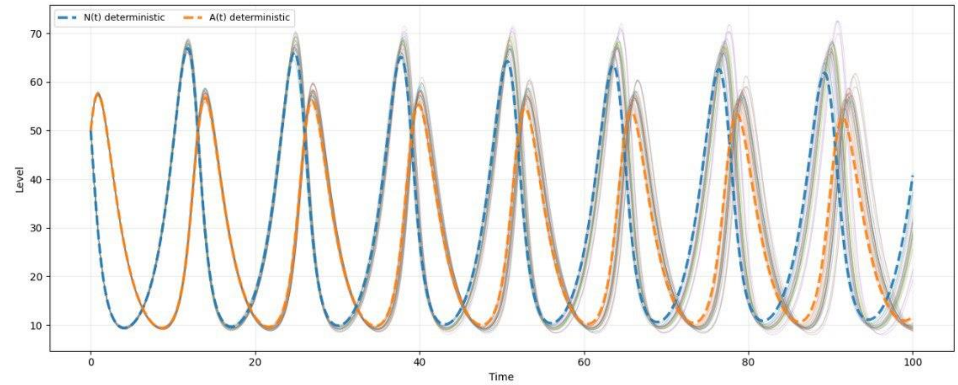

Fig. 7. Rollback manual scenario: deterministic vs stochastic dynamics of $N(t)$ and $A(t)$

The trajectories on the Figure 7 exhibit slightly reduced stochastic variability compared with the previous scenario due to the lower intensity of technological shocks. At the same time, the cyclical interaction between labour and automation remains preserved, indicating that even under slower technological dynamics the system maintains a stable labour–automation feedback structure.

At the initial moment, the distribution of employees across qualification levels is assumed to be the same as in the previous scenarios. Figure 8 illustrates the evolution of this workforce structure in the rollback automation environment. Compared with the previous scenarios, the dynamics exhibit greater temporal variability. The number of senior employees initially increases due to slower forward automation and stronger rollback transitions, but later declines as a result of stochastic shocks and structural adjustments. Lower qualification levels (trainee and junior) gradually decrease, indicating a reduced inflow and slower regeneration of the workforce structure.

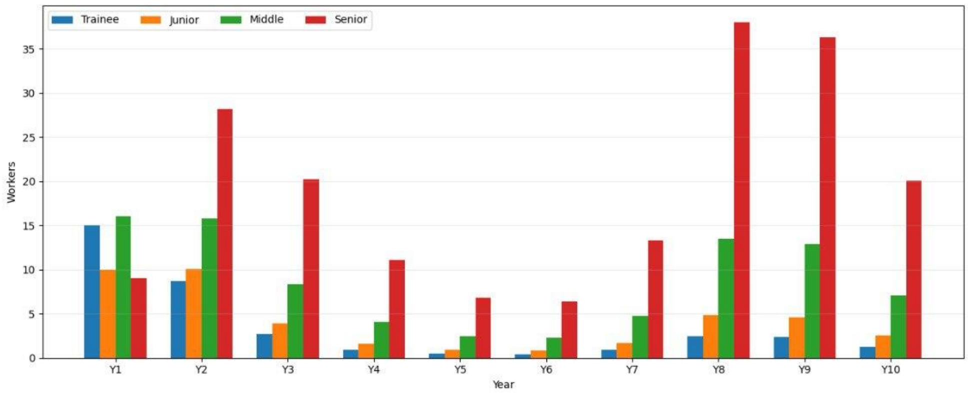

Fig. 8. Rollback manual scenario: workforce structure in the aggregated system

At the initial moment, the distribution of tasks is determined by the stationary distribution of the fast automation process. Figure 9 illustrates the evolution of the task structure in the rollback automation environment. Unlike the previous scenarios, the share of automated tasks decreases over time, while manual and human-assisted tasks become more prominent. Such behavior may occur when technologies become obsolete or less efficient, causing a partial return to human labour.

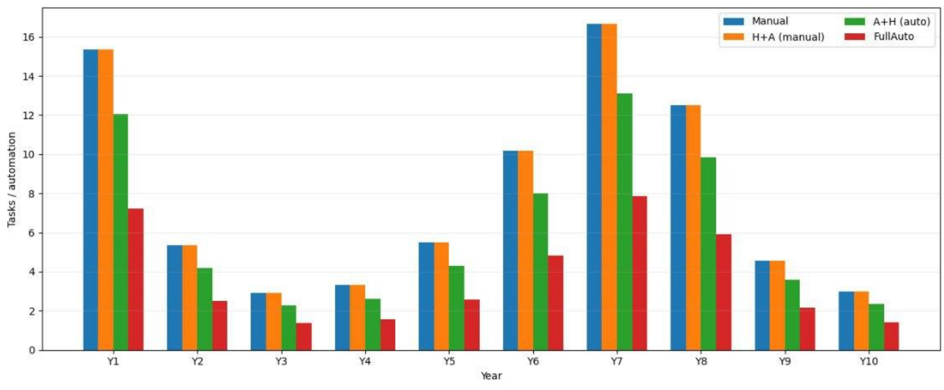

Fig. 9. Rollback manual scenario: task automation structure in the aggregated system

5. Conclusions

In this study, we have developed a comprehensive stochastic evolutionary model to analyze the complex interactions within the technological labor market under the influence of rapid AI advancement. By integrating the classical Lotka-Volterra framework with Markov switching and Levy-type stochastic jumps, we have successfully captured both the continuous dynamics of labor redistribution and the impact of discrete, high-impact «innovation shocks».

The core theoretical contribution of this work lies in the application of the phase merging method within the state space of the system. By employing the formalism of redundant-invertible operators to address the singular perturbation problem, we derived a reduced asymptotic model. This simplification facilitates a more rigorous and tractable analysis of the complex high-dimensional system while preserving the essential qualitative characteristics and asymptotic properties of the original stochastic process. Numerical simulations conducted for three distinct development scenarios – baseline, accelerated automation, and technological rollback – validate the model's performance. The results demonstrate that while stochastic perturbations increase trajectory variability, the underlying cyclical interaction between employment and automation remains robust. Specifically, the accelerated automation scenario indicates a rapid transition toward highly automated tasks and a higher concentration of workforce in senior qualification groups, whereas the rollback scenario exhibits greater structural fluctuations and slower adaptation.

From a strategic perspective, the developed model serves as the mathematical foundation for a decision support system, intended to be implemented as a specialized web application. This tool will allow for the simulation of diverse market trajectories, helping to assess the resilience of strategic sectors against disruptive technological breakthroughs. Future development of this research will focus on expanding the model to incorporate a wider range of external socio-economic factors. A key priority will be the empirical calibration of the model parameters through the synthesis of heterogeneous data from academic literature and open-access databases. Further investigation into the systems stability, the identification of equilibrium points, and comparative analysis with existing market models will ensure the practical reliability of the decision-making tool in conditions of global uncertainty.

References

1. Qamar A., Hall M., Lobo S. The impact of artificial intelligence on labor markets and employment: A systematic review. International Journal of Information Management, 2020, 54, p. 102–135
2. Acemoglu D., Restrepo P. Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 2019, 33 (2), p. 3–30.
3. Peng S., Kalliamvakou E., Cihon P., Demirer M. The Impact of AI on Developer Productivity: Evidence from GitHub Copilot. *arXiv preprint arXiv:2302.06590*, 2023.
4. Handa K., Tamkin A., McCain M., Huang S., Durmus E., et al. Which Economic Tasks are Performed with AI? Evidence from Millions of Claude Conversations. *arXiv preprint arXiv:2503.04761*, 2025.
5. Eloundou T., Manning S., Mishkin P., Rock D. GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. *arXiv preprint arXiv:2303.10130*, 2023.
6. Acemoglu D., Autor D., Hazell J., Restrepo P. Artificial Intelligence and Jobs: Evidence from Online Vacancies. *Journal of Labor Economics*, 2022, 40 (S1), p. S293–S340.
7. Tomlinson K., Jaffe S., Wang W., Counts S., Suri S. Working with AI: Measuring the Applicability of Generative AI to Occupations. *Microsoft Research*, 2024.
8. Autor D. H., Levy F., Murnane R. J. The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 2003, 118 (4), p. 1279–1333.
9. Acemoglu D., Restrepo P. The Race between Machine and Man: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 2018, 108 (6), p. 1488–1542.
10. Brynjolfsson E., Rock D., Syverson C. The Productivity J-Curve: How Intangibles Complement General Purpose Technologies. *American Economic Journal: Macroeconomics*, 2021, 13 (1), p. 333–372.
11. Bass F. M. A New Product Growth for Model Consumer Durables. *Management Science*, 1969, 15 (5), p. 215–227.
12. Volterra V. Leçons sur la théorie mathématique de la lutte pour la vie. 1931, Paris: Gauthier-Villars et Cie.
13. Korolyuk V. S., Korolyuk V. V. Stochastic models of systems. 1999, Dordrecht, The Netherlands: Kluwer Academic Publishers.
14. V.S. Korolyuk, N. Limnios, Stochastic Systems in Merging Phase Space, World Scientific, 2005.
15. Samoilenko I. V., Nikitin A. V. Double merging of the phase space for stochastic differential equations with small additions in Poisson approximation conditions. Cybernetics and Systems Analysis, 2019, 55, p. 265–273.
16. Samoilenko I. V., Nikitin A. V. Double merging of phase space for differential equations with small stochastic supplements under Levy and Poisson approximation conditions. *Annals of the University of Craiova Mathematics and Computer Science Series*, 2020, 47 (1), p. 141–157.
17. Samoilenko I., Nikitin A. Construction features and analysis of warfare information model with Markov switchings under Lévy approximation conditions. Challenges to National Defence in Contemporary Geopolitical Situation, 2020, 2020 (1), p. 209–214.

18. Anisimov V. V. Application of limit theorems for switching processes. Cybernetics, 1978, 6, p. 917–929.
19. Anisimov V. V. Switching processes: averaging principle, diffusion approximation and applications. Acta Applicandae Mathematica, 1995, 40, p. 95–141.
20. Blankenship G. L., Papanicolaou G. C. Stability and control of stochastic systems with wide band noise disturbances. SIAM Journal on Applied Mathematics, 1978, 34, p. 437–476.
21. Nikitin, A., Bekešienė, S., Hošková-Mayerová, Š., & Krasiuk, B. (2024). Multidimensional Model of Information Struggle with Impulse Perturbation in Terms of Levy Approximation. Mathematics, 12(8), 1263.
22. Bekesiene, S., Nikitin, A., & Nechyporuk, S. (2025). Modeling Dynamic Regime Shifts in Diffusion Processes: Approximate Maximum Likelihood Estimation for Two-Threshold Ornstein–Uhlenbeck Models. Mathematics, 13(21), 3450.
23. Samoilenko, I., Nikitin, A., Salo, N., Samoilenko, T., Verovkina, G., & Krasiuk, B. (2024). Information Warfare Model with Internal Conflict. Proceedings of the Challenges to National Defence in Contemporary Geopolitical Situation, Brno, Czech Republic, 11-13.
24. Davis M. H. A. Markov Models and Optimization. Chapman & Hall, 1993.
25. Ethier S. N., Kurtz T. G. Markov Processes: Characterization and Convergence. Wiley, 1986.
26. Freidlin M. I., Wentzell A. D. Random Perturbations of Dynamical Systems. 2nd edition. Springer, New York, 1998.
27. Gihman I. I., Skorohod A. V. Theory of Stochastic Processes. Vol. 1–3. Springer, Berlin, 1974.
28. Glynn P. W. Diffusion approximation. Handbook in Operations Research and Management Science (D. P. Heyman and M. J. Sobel, eds.), 1990, vol. 2, p. 145–198.
29. Iglehart D. L. Diffusion approximations in collective risk theory. Journal of Applied Probability, 1969, 6, p. 285–292.
30. Korolyuk V. S., Limnios N. Diffusion approximation of integral functionals in merging and averaging scheme. Theory of Probability and Mathematical Statistics, 1999, 59, p. 91–98.
31. Korolyuk V. S., Limnios N. Diffusion approximation of integral functionals in double merging and averaging scheme. Theory of Probability and Mathematical Statistics, 2000, 60, p. 87–94.
32. Korolyuk V. S., Limnios N. Evolutionary systems in an asymptotic split state space. Recent Advances in Reliability Theory: Methodology, Practice, and Inference (N. Limnios and M. Nikulin, eds.), Birkhäuser, Boston, 2000, p. 145–161.
33. Korolyuk V. S., Limnios N. Average and diffusion approximation of stochastic evolutionary systems in an asymptotic split state space. *The Annals of Applied Probability*, 2004, 14 (1), p. 489–516.