qisqa va uzoq muddatli resurslarni samarali boshqarish, passivlar tarkibini optimallashtirish va risklarni oldindan aniqlash imkonini beradi.

Ikkinchidan, banklarda raqamli mijozlar ma’lumotlari bazasini markazlashtirish va fintech platformalari bilan integratsiyalashgan data-driven boshqaruv modelini yaratish zarur. Bunday yondashuv AI vositalari yordamida mijozlarni segmentatsiya qilish, individual mahsulotlar taklif etish va xizmatlar sifatini oshirishga xizmat qiladi.

Uchinchidan, kreditlash jarayonida sun’iy intellekt asosidagi kredit skoring va fraud detection tizimlarini bosqichma-bosqich joriy qilish lozim. Bu kredit portfeli sifatini oshirish, nosoz kreditlar ulushini kamaytirish va qaror qabul qilish tezligini sezilarli ravishda yaxshilaydi.

Xulosa qilib aytganda, tadqiqot natijalari banklar faoliyatida sun’iy intellekt vositalarining moliyaviy texnologiyalar va kraudfanding platformalari bilan uygʻunlashuvi Oʻzbekiston bank tizimi uchun istiqbolli yoʻnalish ekanini koʻrsatadi. Bunda raqamli transformatsiya strategiyasi, bank resurs bazasining oʻsishi va mijozlar ma’lumotlari hajmining kengayishi AI yechimlarini bosqichma-bosqich joriy etish uchun muhim asos boʻlib xizmat qiladi. Shu sababli banklarning kelgusi rivojlanishi nafaqat raqamli mahsulotlar sonini oshirishga, balki ularni sun’iy intellekt asosida aqlli boshqarish tizimlari bilan boyitishga ham bogʻliqdir.

Foydalanilgan adabiyotlar roʻyxati:

1) LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444.

2) Oʻzbekiston Respublikasi Prezidenti. (2020). “Raqamli Oʻzbekiston – 2030” strategiyasini tasdiqlash va uni samarali amalga oshirish chora-tadbirlari toʻgʻrisida”gi PF-6079-son Farmon. 5-oktabr, 2020-yil.

3) Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. Journal of Banking & Finance, 34(11), 2767–2787.

4) Thakor, A. V. (2020). Fintech and banking: What do we know? Journal of Financial Intermediation, 41, 100833.

5) Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. Journal of Business Venturing, 29(5), 585–609.

6) www.nbu.uz Oʻzbekiston Respublikasi Tashqi iqtisodiy faoliyat Milliy banki ma’lumotlari

A SEMI-MARKOV–HAWKES APPROACH TO MANAGING THE MECHANISM OF A SELF-ORGANIZING TRADING SYSTEM

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Abstract: *This paper proposes an integrated approach based on Semi-Markov and Hawkes processes to model the internal mechanisms of a self-organizing trading system. Traditional market microstructure models typically analyze either the irregularity of inter-trade durations or the mutual excitation effects between trades. In this study, to more accurately capture real market dynamics, a unified probabilistic framework incorporates stochastic inter-trade durations, clustering of trading intensity, daily trading patterns, trade volume, and location factors.*

Keywords: *Semi-Markov process, Hawkes process, trading system, self-organization, market microstructure, trading intensity, clustering, liquidity.*

Market components such as prices, trading volume, and consumer opinions exhibit a high degree of variability. Such variability leads to strong fluctuations over short time intervals. In classical regression models, only the mean values, trends, or seasonal components of these variables are estimated; however, the impact of previous trading decisions on future trades is not assessed from an economic, statistical, or empirical perspective. In general evaluations, the self-organizing property of the trading system is not taken into account[279].

In modeling a self-organizing trading system, the Semi-Markov–Hawkes approach focuses on a point process framework, since the trading system operates through a sequence of discrete events over time. In such a system, these events may include trade executions, order placements, price changes, the introduction of new products, intensification of external influences, and other similar occurrences.

Below, we present Definitions 1 and 2 based on source[280]

Definition1. We consider market trades as a point process occurring at time moments $\{T_i\}_{i\geq 1}$. If the number of trades observed in the interval $[0,t]$ is denoted by $N(t)$, then:

$$N(t) = \sum_{i\geq 1} 1_{\{T_i \leq t\}} \quad (1)$$

where $1_{\{\cdot\}}$ – is the indicator function.

From Definition (1) it follows that the indicator function assigns the value 1 to every event that occurred up to time t, and 0 otherwise, thereby capturing the total number of trades realized by time t. Since a specific event occurs at time T_i, we are interested in determining the probability that the next event will occur in the near future. For this purpose, we introduce the intensity function.

Definition 2. (Intensity function). The conditional intensity of a point process is defined as:

$$\lambda(t|\mathcal{F}_t) = \lim_{\Delta t \to 0} \frac{E[N(t+\Delta t) - N(t)|\mathcal{F}_t]}{\Delta t} \quad (2)$$

where $\mathcal{F}_t$ denotes the sigma-algebra containing all information about events observed up to time t, and satisfies the filtration property $\mathcal{F}_s \subseteq \mathcal{F}_t$ for all $s < t$. In financial markets, information regarding products, prices, or trading activity is continuously updated and accumulated; therefore, $\{\mathcal{F}_t\}_{t\geq 0}$ represents the growing information set.

Now, assuming that the occurrence of a particular event increases the likelihood of future events, we introduce the fundamental definition of the **Hawkes process**, which characterizes a self-exciting system.

Definition 3 (Hawkes process). A self-exciting Hawkes process is defined as follows:

$$\lambda(t) = \mu(t) + \int_0^t \phi(t-s)dN(s) \quad (3)$$

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[279] Rambaldi, M., Bacry, E., Lillo, F. Modeling market microstructure with Hawkes processes. Quantitative Finance, 2017y., 17(7), 999–1020. Sornette, D. Self-organization in financial markets. Springer Complexity. 2014y.

[280] Swishchuk, A. Semi-Markov models for financial markets. Springer. 2013y. Daley, D. J., Vere-Jones, D. *An Introduction to the Theory of Point Processes: 2003y., Volume I–II.* Springer.

where : $\mu(t)$ −denotes the baseline (daily) intensity, and $\phi(t-s)$ −is the kernel function describing the excitation effect of past events on future arrivals.

Definition 4 ([15]). Let $E = \{1,2,\dots,K\}$ be a discrete set of states. A pair (X_n, T_n) is called a Semi-Markov process if

$$P(X_{n+1} = j, T_{n+1} - T_n \leq t \big| X_n = i, \mathcal{F}_{T_n}) = Q_{ij}(t) \ (4)$$

where $Q_{ij}(t)$ − is the distribution function describing the transition from state i to state j, and $T_{n+1} - T_n$ denotes the waiting time (sojourn time) in state iii, which may follow an arbitrary probability distribution[281].

In the methodology, we model the self-organizing trading system using a Semi-Markov–Hawkes process through the following system:

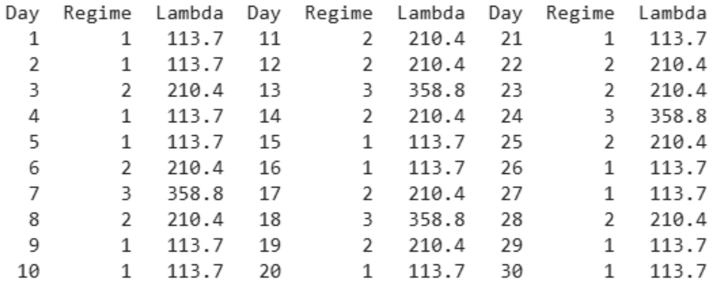
$$\begin{cases} Q_{ij}(t) = p_{ij} G_{ij}(t), \\ X_t = X_n \ agar \ T_n \leq t < T_{n+1} \\ \lambda(t) = \mu X_t + \int_0^t \phi_{X_s X_t}(t-s) dN(s) \\ \lim\limits_{t\to\infty} P(X_t = j) = \pi_j \end{cases}$$ [282]

Using this system, we conducted a 30-day observation in the farmers' market located in Nukus city for three products (flour, meat, and chicken eggs).

We determine the values of the intensity function and present the results in table 1 below:

Table 1

Daily conditional intensity values $\boldsymbol{\lambda(t|\mathcal{F}_t)}$

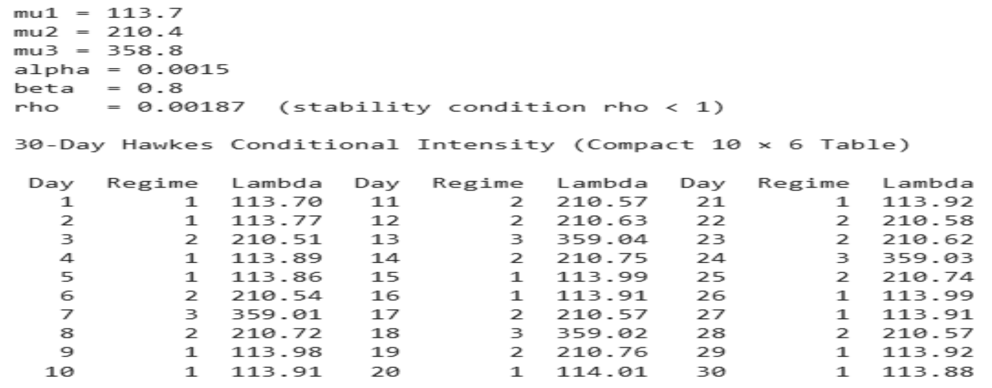


```
Day  Regime  Lambda  Day  Regime  Lambda  Day  Regime  Lambda
  1       1   113.7   11       2   210.4   21       1   113.7
  2       1   113.7   12       2   210.4   22       2   210.4
  3       2   210.4   13       3   358.8   23       2   210.4
  4       1   113.7   14       2   210.4   24       3   358.8
  5       1   113.7   15       1   113.7   25       2   210.4
  6       2   210.4   16       1   113.7   26       1   113.7
  7       3   358.8   17       2   210.4   27       1   113.7
  8       2   210.4   18       3   358.8   28       2   210.4
  9       1   113.7   19       2   210.4   29       1   113.7
 10       1   113.7   20       1   113.7   30       1   113.7
```

The following table presents the Hawkes intensity values determined using the corresponding parameter estimates (table 2):

Table 2

Hawkes intensity values $\boldsymbol{\lambda(t)}$



```
mu1  = 113.7
mu2  = 210.4
mu3  = 358.8
alpha = 0.0015
beta  = 0.8
rho   = 0.00187  (stability condition rho < 1)

30-Day Hawkes Conditional Intensity (Compact 10 × 6 Table)

 Day   Regime   Lambda   Day   Regime   Lambda   Day   Regime   Lambda
   1        1   113.70    11        2   210.57    21        1   113.92
   2        1   113.77    12        2   210.63    22        2   210.58
   3        2   210.51    13        3   359.04    23        2   210.62
   4        1   113.89    14        2   210.75    24        3   359.03
   5        1   113.86    15        1   113.99    25        2   210.74
   6        2   210.54    16        1   113.91    26        1   113.99
   7        3   359.01    17        2   210.57    27        1   113.91
   8        2   210.72    18        3   359.02    28        2   210.57
   9        1   113.98    19        2   210.76    29        1   113.92
  10        1   113.91    20        1   114.01    30        1   113.88
```

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[281] Collet, Martinez, San Martín. *Quasi-stationary distributions: Markov chains, diffusions and dynamical systems,* Springer. 2015y. **Limnios Oprisan.** Semi-Markov Processes and Reliability/ Birkhäuser Boston 2001. https://doi.org/10.1007/978-1-4612-0161-8

[282] Limnios Oprisan. Semi-Markov Processes and Reliability/ Birkhäuser Boston 2001. https://doi.org/10.1007/978-1-4612-0161-8

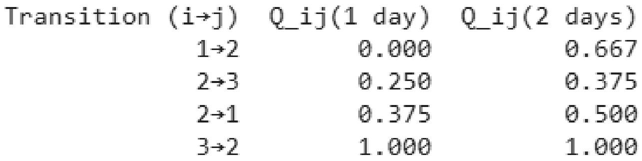
In the next stage, we calculate the semi-Markov transition probabilities. For this purpose, we use table 1. According to the data, the transition $X_1 \rightarrow X_2$ occurred 6 times, while $X_1 \rightarrow X_1$ occurred 7 times. Following the same logic, the transitions $X_2 \rightarrow X_1$ occurred 6 times, $X_2 \rightarrow X_2$ occurred 2 times, and $X_2 \rightarrow X_3$ occurred 2 times. Similarly, the transition $X_3 \rightarrow X_1$ did not occur, $X_3 \rightarrow X_2$ occurred only once, and $X_3 \rightarrow X_3$did not occur. As a result, we determined the following transition probabilities:

$$P = \begin{pmatrix} 0.538 & 0.462 & 0 \\ 0.6 & 0.2 & 0.2 \\ 0 & 1 & 0 \end{pmatrix} \quad (17).$$

After determining the transition probabilities, the semi-Markov sojourn time (duration) is calculated, and as a result, the values of the transition distribution function are obtained (table 5):

Table 3

Values of the transition distribution function



```
Transition (i→j)  Q_ij(1 day)  Q_ij(2 days)
             1→2        0.000         0.667
             2→3        0.250         0.375
             2→1        0.375         0.500
             3→2        1.000         1.000
```

From table 5 presented above, we observe that $T_{max} = 2$, since the maximum transition duration was two days (see table 1). Using the transition probabilities (16) and the mean sojourn times ($m_1 = 2, m_2 = 1{,}2, m_3 = 1$), we determine the stationary distribution of the embedded Markov chain as $\hat{\pi} = (0.52,\ 0.40,\ 0.08)$. Then, according to the theorem, the stationary distribution of the semi-Markov process is obtained as $\pi = (0.65,\ 0.30,\ 0.05)$.

In this discrete-time Semi-Markov–Hawkes model, three states were analyzed: 1 – low volatility,2 – medium volatility, and 3 – high volatility. Based on empirical data, the Markov transition matrix was constructed. The results show that the probability of the market remaining in state 1 is higher compared to the other states. Observations indicate that transitions from state 2 to state 1 occur relatively frequently. The third state was found not to be independent, as it quickly transitions to state 2. The average sojourn time in each state was determined to be 2 days for state 1, 1.2 days for state 2, and 1 day for state 3. From these average durations, it can be concluded that the low-volatility state is relatively stable, whereas the high-volatility state is short-term and highly dynamic. Since the conditions of the theorem are satisfied, the long-run distribution of the system indicates that the process spends 65% of the time in state 1, 30% in state 2, and 5% in state 3. Therefore, the model demonstrates that the market predominantly operates around low and medium activity levels, while high activity is rare and short-lived.

References:

1. *Rambaldi, M., Bacry, E., Lillo, F. Modeling market microstructure with Hawkes processes. Quantitative Finance, 2017y., 17(7), 999–1020.*
2. *Sornette, D. Self-organization in financial markets. Springer Complexity. 2014y.*
3. *Swishchuk, A. Semi-Markov models for financial markets. Springer. 2013y.*
4. *Daley, D. J., Vere-Jones, D.* An Introduction to the Theory of Point Processes: 2003y., Volume I–II. *Springer.*