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MANAGEMENT OF THE INTENSITY OF THE FLOW OF BUYERS OF THE RETAIL NETWORK

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Abstract. An approach to the management of customer flows is considered, which takes into account the uniformity of the daily intensity as an efficiency criterion. An intensity model is proposed to assess the degree of uniformity. A new formulation of the task of managing the flow of buyers has been introduced, the main feature of which is the criterion of management efficiency, based not on the economic effect, but on the uniformity of the flow. At the same time, the time of making a purchase is, as a rule, a random value. Then the ratio of the instantaneous intensity of the flow and its power per day is the probability of visiting the store at a certain point in time. The relative intensity thus specified can be examined using the density function of the purchase time distribution. To assess uniformity, it is suggested to switch to the daily flow intensity model. The built map of the cluster structure of flows allows you to visually analyze the effectiveness of managing the intensity of customer flows, in particular, during peak pricing activities. The economic effect is justified by the economic benefit, which is achieved not only due to the equalization of the intensity of the purchase flow during the day, but also due to the increase in the volume of sales, which compensates for the reduction of the mark-up in periods of low purchase activity. Therefore, along with the relative intensity, changes in the power of the flow and its qualitative composition according to the average purchase volume were also studied. The purpose of the study is to assess the effectiveness of peak pricing measures in terms of smoothing daily fluctuations in the intensity of the flow of buyers in retail chains. To achieve the goal, a new formulation of the task of managing the flow of buyers was introduced, the main feature of which is the criterion of management efficiency, based not on the economic effect, but on the uniformity of the flow. To assess such uniformity, it is suggested to switch to the daily flow intensity model. It is important to take into account the relationship between the characteristics of the structural components of the flow on one of the components leading to a change in the intensity of the other. In general, the proposed formulation of the task of flow management and the model of its intensity are also applicable in the activities of companies of other types of economic activity that face the problem of peak demand, for example, in the electric power sector. This opens up opportunities to identify new patterns in consumer behavior.

Keywords*:* purchase flow, model, intensity, trade, purchase, pricing.

JEL Classification: G11, G13, G32

1. INTRODUCTION

In many types of economic activity, the demand for goods and services is subject to periodic fluctuations of various nature (seasonal, cyclical, etc.). The observed repeatability of such fluctuations allows industrial and commercial enterprises to adjust the planned volumes of production and sales, varying the used production capacities, trading areas and the number of service personnel. However, this entails the unevenness of the material, personnel and related flows of the organization, which increases the costs generated by the movement and regulation of such flows. The desire to reduce such costs presents the management of enterprises with the important task of smoothing out fluctuations in demand and the intensity of purchase flows. However, there is currently no clear formal definition of this management task, so research in this direction seems relevant.

In order to compensate for the increasing marginal costs in periods of maximum demand, pricing is applied taking into account the peak load (Aiman et al., 2016), which consists of setting higher prices in such periods. This tactic has become widespread in the energy sector of passenger transportation, in the service sector. It is traditionally assumed that marginal costs and sales volumes in peak and typical periods are independent. As a result, it is possible to substantiate the economic effect of the considered pricing tactics due to the assignment of consumer surplus.

However, in a number of types of economic activity, the intensity of flows of buyers in periods of low and high activity are interconnected. Thanks to the tactics of peak pricing (for example, in electricity), it is possible to redistribute the load from the peak time to the time of less intensive consumption. For other areas, similar effects are not covered in the scientific literature, although the study of the impact of peak pricing on the uniformity of purchasing flows of trading companies is of great importance from the point of view of regulating the loading of service personnel. Thus, the purpose of the study is to evaluate the effectiveness of peak pricing measures in terms of smoothing daily fluctuations in the intensity of the flow of buyers in retail chains.

To achieve the goal, a new formulation of the task of managing the flow of buyers was introduced, the main feature of which is the criterion of management efficiency, based not on the economic effect, but on the uniformity of the flow. To assess such uniformity, it is suggested to switch to the daily flow intensity model.

2. THEORETICAL BACKGROUND

Consider the model of the intensity of the flow of buyers. Flow intensity is defined as the average number of customers per unit of time. At the same time, the time of purchase is usually a random value (Chetan & Indira, 2020). Then the ratio of the instantaneous intensity of the flow and its power per day is the probability of visiting the store at a certain point in time. The relative intensity thus specified can be examined using the density function of the purchase time distribution (Haghani et al., 2014).

Due to the specifics of trade statistics, we will use the share of customers served at a certain time in their number per day as an estimate of the probability of purchase (Hu et all 2018). For the most part, data on the number of punched checks is automatically accumulated during such time intervals in many retail chains. At the same time, it is convenient to consider the flow of purchases precisely as an output flow, since the characteristics of the incoming flow, as a rule, are not recorded in reporting (Igwe et all 2014).

3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

Based on the results of the average relative frequency of visiting the store for a certain time, you can build an empirical analog of the density function - a polygon of frequencies. It reflects the change in the intensity of the real flow of buyers. Analyzing a large number of similar polygons by different stores, time periods and days of the week, some similarities in the type of shopping time distribution were found. Thus, as a rule, two attendance peaks can be traced on the frequency polygon, which indicates a bimodal distribution law (Kritchanchai & Hoeur 2018). Apparently, the first peak hour corresponds to the most popular time for customers to visit the day stream, and the second to the evening stream. So, in the structure of the general purchase flow, two components with different features of the intensity of the arrival of customers during the day are distinguished (Karthik 2016).

The considered polygon of frequencies allows us to give a clear graphical interpretation of the characteristics of the purchase flow. However, this representation is very inconvenient for comparing the forms of distributions of the probability of purchase in both spatial and temporal sections, as it operates with a whole range of relative frequencies that are stochastic in nature (Li et all 2016). Using normal sample estimates of the mean and standard deviation to characterize distributions is not enough, as it does not allow taking into account the heterogeneity of the flow of buyers. Therefore, it is suggested to proceed to the construction of a probability model of the intensity of the flow of customers (Kelly & Yudovina 2015).

4. RESULTS AND DISCUSSION

When choosing the form of the model, the heterogeneity of the structure of the purchase flow is reflected through the representation of the time of day ξ and the time chosen for visiting the store, by superposition of a set of n random variables, {ξ_i }_(i=1)^neach of which is implemented with probability k i and reflects the corresponding component of the flow. Since the purchase time t is limited to a certain interval that depends on the mode of operation of the outlet, i.e. t ∈ [a;b], where a, b are the opening and closing times of the store, respectively, the model of the intensity of the flow of customers is proposed to be presented in the form of a combination of normal distributions:

$$f(t) = \sum_{i=1}^{n} k_i \frac{f_i(t,\mu_i,\sigma_i)}{F_i(a,b,\mu_i,\sigma_i)}, \quad \sum_{i=1}^{n} k_i = 1, \qquad (1)$$

where $\frac{f_i(t,\mu_i,\sigma_i)}{F_i(a,b,\mu_i,\sigma_i)}$the intensity of the i-th flow of customers, which is given by the density function of the normal distribution $f_i(t,\mu_i,\sigma_i)$with mathematical expectation $\mu_i$and variance $\sigma_i$and $F_i(a,b,\mu_i,\sigma_i)$the probability of visiting the store in the time interval [a; b] of the form

$$F_i(a,b,\mu_i,\sigma_i) = \Phi\left(\frac{b-\mu_i}{\sigma_i}\right) - \Phi\left(\frac{a-\mu_i}{\sigma_i}\right), i = \overline{1,n}.$$

Here, Φ(z) stands for the standard normal distribution function. In Figure 1, in our case, mainly two streams are distinguished (day and evening), therefore, n=2. At the same time, the parameters of the intensity model (1) have an obvious meaningful interpretation: μ_i is the time of maximum intensity of the itch flow of customers; σ_i is an indicator of the dispersion of the time of visiting the store by buyers of the itch flow, and the majority of such customers come during the period of time $[\mu_i - \sigma_i; \mu_i + \sigma_i]$their specific weight in the total number of buyers of the i-th flow is, on average, approximately $\frac{0.683}{F_i(a,b,\mu_i,\sigma_i)}$the share of buyers of the i-th flow in the total flow of buyers.

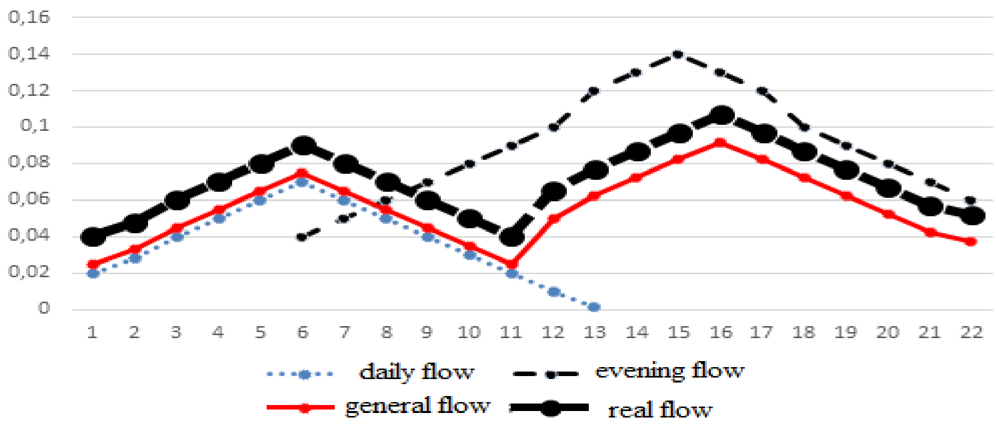

Fig. 1. The results of the identification of the model of the intensity of the flow of buyers

Thus, model (1) allows us to describe the observed heterogeneity of the overall customer flow. At the same time, the change in intensity of each structural component of the flow is specified using only three parameters. As a result, we get a convenient tool for analyzing changes in the characteristics of the purchase flow depending on peak pricing measures.

The data on the number of checks every hour served as the empirical basis of the study:

− at one point in time (December 2023) for 90 stores of a retail chain located in the Ivano-Frankivsk region;

− in one of the stores in Ivano-Frankivsk for the period from January 2023 to December 2023, in which, in order to encourage customers to visit more intensively in the morning, from July 2023, additional discounts on most products began to be provided on weekdays from 8 a.m. to 12 p.m. hours

Based on these data, the intensity model (1) was identified for each store on average per month for each day of the week separately. For parameter estimation, the $\chi 2$ method [4] was chosen as the simplest in numerical implementation. Due to its sensitivity to anomalous observations, the analyzed samples exclude days in which there were any failures in the service system. As an alternative option, it is recommended to resort to sustainable evaluation methods (Nityangini & Pravin 2017).

Smoothed lines in fig. Figure 1 shows the values of the intensity of the buying flow restored by model (1) on Mondays in April 2023. It can be seen that the model is in good agreement with the original data. Formally, its significance is confirmed by testing the agreement hypothesis using the $\chi 2$ test. In the considered example, this hypothesis cannot be rejected with a 75% actual level of significance. The results of the identification of model (1) according to all the data made it possible to identify certain regularities in the change in the parameters of the intensity of the purchase flow.

Let's move on to the consideration of shopping rhythms. Publications (Kritchanchai & Hoeur 2018) consider the concept of shopping rhythms, which involves the habits developed by consumers regarding the frequency of store visits and the volume of purchases made there. In this context, this concept can be associated with the intensity of the purchase flow over a certain long period of time (a week, a month). Reducing this interval to an hour, we will use the term "daily shopping rhythms", which will reflect the preferences of buyers regarding the time of day of visiting the store.

The identification of the intensity model based on time data allows us to study the dynamics of such benefits. To do this, we will operate with the dynamic series of the obtained estimates of model parameters (1).

A visual analysis of the graphs of these series in Figure 2 shows the seasonal nature of the change in indicators.

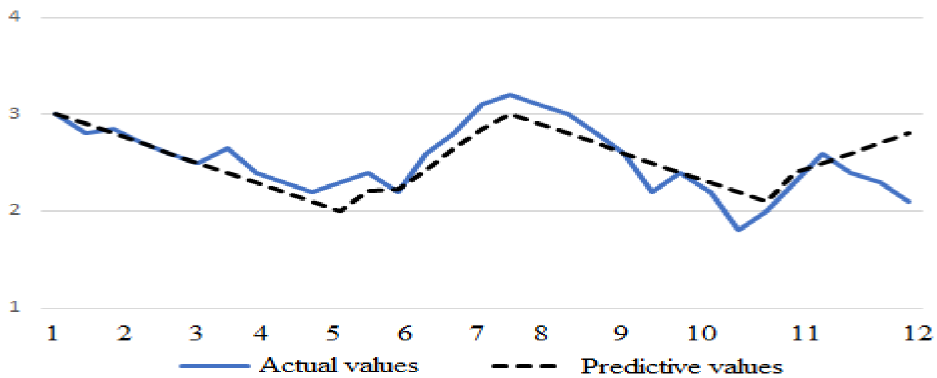

Fig. 2. Seasonal fluctuations of model estimates of intensity model parameters

Periodic fluctuations are especially clearly visible in the dynamics of the intensity of the purchase flow in the evenings and on weekends, since the impact of peak pricing measures was felt here to a lesser extent. The dynamics of parameter estimates for the morning stream on weekdays is characterized by a pronounced trend caused by the influence of marketing stimulation. Therefore, the following schedule of the time series of the intensity parameters is proposed:

$$y=\alpha+\beta\tau+\gamma\sin\varrho\tau+\varepsilon, \tag{2}$$

where α, β, γ are parameters to be estimated,

τ - time, months;

$\varrho = \pi/6$, since the period is 12 months;

ε is a random error.

Identification of model (2) for each day of the week was performed using the method of least squares. The results of parameter estimation and their significance are shown in Tab. 1.

Tab. 1

Estimation of the distribution of the time series of the intensity parameters

Indicator	Rating	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
$\hat{k}_1$	$\hat{\alpha}$	0.37	0.37	0.37	0.33	0.3	0.47	0.5
	$\hat{\gamma}$	-	-	-	-	-	0.22	0.13
$\hat{\mu}_1$	$\hat{\alpha}$	12.9	12.8	12.9	12.7	12.5	13.5	13.4
	$\hat{\beta}$	-0.09	-0.07	-0.09	-0.08	-0.09	-0.02	0.02
	$\hat{\gamma}$	0.4	0.2	0.21	0.17	0.3	1.06	0.9
$\hat{\sigma}_1$	$\hat{\alpha}$	3.26	3.24	3.31	3.29	3.3	3.71	3.62
	$\hat{\beta}$	-0.05	-0.03	-0.05	-0.05	-0.06	-	0.2
	$\hat{\gamma}$	0.61	0.53	0.51	0.47	0.53	1.02	0.97
$\hat{\mu}_2$	$\hat{\alpha}$	20.4	20.4	20.3	20.2	20.1	20.3	20.2
	$\hat{\gamma}$	0.73	0.71	0.72	0.69	0.76	1.63	1.31
$\hat{\sigma}_2$	$\hat{\alpha}$	2.61	2.6	2.59	2.6	2.8	2.7	2.6
	$\hat{\gamma}$	-	-	-	-	-	-0.71	-0.44

According to the found estimates, $\hat{\alpha}$ it is possible to conclude about significant differences in the average intensity of customer flows on weekdays and weekends. So, on weekdays, the evening stream is significantly predominant; the share of buyers during the day is on average 0.14 lower than at the weekend. At the same time, on average, weekday shoppers come earlier and are more concentrated around peak hours. No such strong differences were found for the evening stream. Probably, the observed features are due to the influence of peak pricing.

As for the parameters of the daily flow, only the spread of the time of visiting shops is significantly different on weekdays. On weekends, it is on average 52 minutes shorter than on weekdays.

In addition, across all outlets, on the contrary, the parameters of the evening flow of customers differ significantly by day of the week: on weekends $\hat{\mu}_2$there are fewer than on weekdays, but $\hat{\sigma}_2$more. Therefore, the parameters of the intensity model behave differently depending on the characteristics of the stores, so both spatial and temporal data are used to identify relationships between them.

Secondly, the significance of seasonal fluctuations of the intensity parameters was confirmed, while $\hat{\gamma} > 0$ indicates an increase in the values of the series in the summer season, and $\hat{\gamma} < 0$ - a decline (see Table 2). This makes it possible to supplement the previously obtained results about the usual purchase rhythms of customers of a retail trade enterprise:

- in the summer period, as a rule, most consumers come to the store later in the evening, the spread of visiting time increases during the day, and decreases in the evening on weekends;

- in the winter season, on average, customers prefer to come to the store earlier in the evening, the spread of shopping time during the day decreases, and increases in the evening on weekends.

It can be argued that the trend estimates $\hat{\beta}$ are significant only in models of the dynamics of estimates of the parameters of the model of the intensity of the daily flow of buyers on weekdays. Moreover, $\hat{\mu}_1$they $\hat{\sigma}_1$are decreasing, which is explained by the effect of the discounts provided: most customers try to come to the store in the morning so that they have time to take advantage of the discount on the promotion. Therefore, the daytime peak time is moved to an earlier time, and a larger share of buyers is concentrated in the area of this time interval. Time series of estimations of intensity model parameters obtained after exclusion of trend and seasonal components are used to identify the relationship between them.

Interrelation of flow intensity model parameters. Correlation analysis of estimates of flow intensity model parameters for each day of the week separately (according to temporal and spatial data) indicated the existence of their close relationship. All pairwise correlation coefficients [8] were significant at the 1% level. For a more detailed analysis, partial correlation coefficients were calculated between pairs of parameter estimates excluding the influence of all others, as well as the influence of store location (in a city or village) for spatial data.

Values at the 5% level of partial correlation coefficients as a whole for all weekdays are shown in Figure 3. The solid lines depict relationships revealed by time data. Estimates of coefficients are given in italics. Dashed lines correspond to correlations detected only from spatial data, for which coefficient estimates are given in parentheses. Bold lines are relationships confirmed by both spatial and temporal data. Based on the correlations between the estimates, it is possible to draw a conclusion about the strength and direction of the relationship between the parameters.

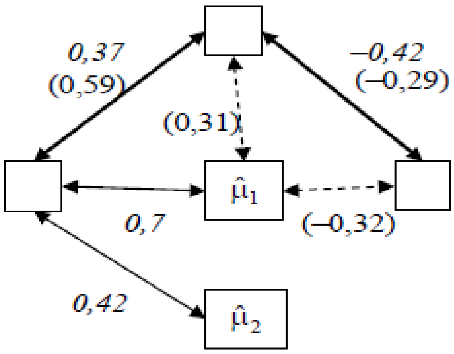

Fig. 3. Partial correlations between estimates of flow intensity model parameters

Since $k_2=1-k_1$, the partial correlation coefficients between $\hat{k}_1$and other parameter estimates, taken with the opposite sign, reflect the relationship $\hat{k}_2$with $\hat{\sigma}_1, \hat{\sigma}_2$and $\hat{\mu}_1$. Therefore, direct relationships are observed between the share of buyers of each stream in the total stream, on the one hand, and the spread of the time of day of making a purchase by customers of this stream, on the other.

The identified correlational relationships between flow intensity parameters should be taken into account when developing measures involved in their regulation, in particular, peak pricing tactics. Thus, shifting the daytime peak hour by providing discounts in the morning causes a direct decrease in the spread of daytime shopping times (the strongest correlation) and an increase in the variation in the time of visiting the store in the evening. While the specific weight of buyers of the daily flow with a decrease in μ_1 should decrease on average. If, on the contrary, the measures are aimed at changing the evening peak hour μ_2, it will affect only the parameter σ_1 of the dispersion of the visit time during the day.

It can be argued that almost all parameters of the intensity model have a complex effect when regulating the daily purchase flow of a retail trade network. However, the final effect depends on how changing these parameters affects the uniformity of the flow of customers. To answer this question, let's move on to setting the task of managing the purchase flow.

Having previously defined its uniformity as a criterion for the effectiveness of managing the flow of customers, let's take the simplest indicator that characterizes the uniformity of the daily intensity of the flow, namely the dispersion D (ξ) of the time of day of visiting a retail outlet. In general, it is usually the case that the more dispersed the flow is in time, the more uniform it is. Then the management task can be formulated as follows:

$$D(\xi) \to \max \qquad (3)$$

with restrictions on the parameters of the density function of the random variable ξ, which arise due to their interdependence (see Fig. 3), as well as due to the fixed time of operation of the store [a, b]. In order to express the objective function of problem (3) through the entered parameters of the flow intensity model, using the results given in [11] for the truncated normal distribution, an expression for the variance of the random variable ξ, which is represented by a combination of truncated normal distributions (1), with n = 2:

$$D(\xi) = k_1\sigma_1^2 + k_2\sigma_1^2 + k_1k_2\Delta\mu^2 + \zeta \quad (4)$$

ζ- the stochastic component that arises as a result of the finiteness of the distribution ξ.

Due to the small probability of visiting the store during the hours of opening and closing by customers of the i-th flow, the value ζ does not have a decisive effect on the flow uniformity criterion (4). It always acquires negative values, since the truncated distribution is characterized by a smaller spread. At the same time, the absolute value of the fraction ζ in D(ξ) according to temporal data is on average about 15%, according to spatial data - approximately 20%. In the following, we will neglect this component, since it is not possible to separate the influence of each parameter of the flow intensity model. The difference between the evening and daytime peak hours Δμ has the greatest influence on the variance. Therefore, peak pricing tactics aimed at stimulating earlier visits to the store leads to an increase in Δμ, thereby increasing the efficiency of managing customer flows according to criteria (3) - (4).

1 and σ_1, σ_2 is indicated . To do this, taking into account the fact that $k_2=1-k_1$, we will make the following transformations:

$$k_1\sigma_1^2 + k_2\sigma_2^2 = k_1(\sigma_1^2 - \sigma_2^2) + \sigma_2^2 = k_1(\sigma_1^2 - \sigma_2^2)(\sigma_1^2 + \sigma_2^2) + \sigma_2^2 (5)$$

Since μ_1 is multidirectionally interconnected with σ_1 and σ_2, the final change in the value of the weighted sum of variances (5) remains undefined and depends on the initial values of the spread of the time of day visiting the store by different flows of customers and the ratio between them. Since σ_2 practically does not change over time (see Tab. 1) and varies much less among stores compared to σ_1, as the main indicator that determines dispersion, by analogy with Δμ, we will choose the difference in the variation of the time of purchase Δσ.

In general, the effect of managing the shopping flow is ambiguous and depends on the combination of values of the flow intensity model parameters in a particular store. Therefore, when planning and analyzing peak pricing measures, it makes sense to group stores of a retail chain that reflects the differences in the ratio of these parameters Δμ, Δσ.

Consider the cluster structure of customer flows. The proposed indicators of the evenness of the flow of customers were used to divide the stores of the retail network under consideration into clusters depending on the flow intensity parameters. For this purpose, estimates of Δμ, Δσ values for each day of the week and store are determined based on spatial data. Then, using the method of principal components [8], two latent factors F_1 and F_2 were selected , which describe 40 and 22% of the variance of the analyzed indicators, respectively. The results are shown in Tab. 2.

Based on the found factor loadings on the basis of Table 2, it can be concluded that the factor F_1 mainly determines the difference in the indicators of the dispersion of the time of visiting the store by buyers of daytime and evening streams. To understand its meaningful essence, paired and partial correlations were analyzed between the hidden factor and the characteristics of the stores of the retail chain: the average monthly number of customers, the average check, area, mark-up, location, number of cash registers. When false correlations were excluded, the dependence of F_1 on the location of the store in an urban or rural area (Spearman's correlation coefficient [8] significance level at the 1% level) and area when excluding the influence of location (partial correlation coefficient [8] significance level at 5% level). Therefore, the differentiation of stores of the retail network is related to their scale according to the first factor. The second factor F_2 determines the difference between daytime and evening peak hours on weekdays (see Tab. 2).

Tab. 2

Results of factor analysis

Weekday	Rating parameter	Factor loads		Schedule coefficients	
		F1	F2	F1	F2
Monday	$\Delta\hat{\mu}$	0.091	0.802	0.022	0.296
Tuesday	$\Delta\hat{\mu}$	0.009	0.875	0.001	0.272
Wednesday	$\Delta\hat{\mu}$	0.034	0.901	0.005	0.281
Thursday	$\Delta\hat{\mu}$	0.037	0.757	0.009	0.297
Friday	$\Delta\hat{\mu}$	0.099	0.873	0.028	0.278
Saturday	$\Delta\hat{\mu}$	0.421	0.083	0.052	0.026
Sunday	$\Delta\hat{\mu}$	0.542	0.182	0.091	0.043
Monday	$\Delta\hat{\sigma}$	0.901	-0.162	0.152	-0.054
Tuesday	$\Delta\hat{\sigma}$	0.908	-0.171	0.165	-0.057
Wednesday	$\Delta\hat{\sigma}$	0.893	-0.223	0.161	-0.081
Thursday	$\Delta\hat{\sigma}$	0.909	-0.137	0.172	-0.051
Friday	$\Delta\hat{\sigma}$	0.906	0.112	0.171	-0.053
Saturday	$\Delta\hat{\sigma}$	0.892	0.257	0.158	0.081
Sunday	$\Delta\hat{\sigma}$	0.791	0.273	0.127	0.089

At the same time, with increasing $F_{2\ values}$, the time of the evening peak hour on weekdays practically does not change. From this it can be concluded that the second factor inversely proportionally affects the most popular time of store visits by day flow on weekdays. It is not related to the previously mentioned characteristics of stores, so the only explanation for its existence is the existence of heterogeneity of buyers. Some customer flows, corresponding to large values of F_2, have a greater intensity during the day on weekdays in the early hours (on average from 11:30 a.m. to 1 p.m.), and others already at lunchtime (usually from 12:30 p.m. to 14 hours). Based on the proximity of most stores of the second group (with lower $F_{2values}$) to business centers and administrative buildings, it is concluded that their daytime customers are mainly office workers who buy products for their lunch break. So, perhaps the second factor reflects the ratio in the daily purchasing flow of housewives and office workers.

In general, the increase in the values of the first and second factors indicates an increase in the level of uniformity of daily customer flows, therefore the obtained results are applicable to achieve the goal of assessing the effectiveness of peak pricing measures. Along with this, they can be useful for predicting the intensity of purchase flows of new stores based on their characteristics and location. For a visual representation of the stores of the retail network, it is convenient to imagine two selected factors in space. The observed differentiation makes it necessary to distinguish some homogeneous groups of stores similar in terms of the intensity of customer flows. For this purpose, cluster analysis was used on F1 and F2 factors.

Using the K-means method (Kritchanchai & Hoeur 2018), taking into account the share of the explained variance of each of the factors of the intensity model, four clusters were obtained (Fig. 4). They are given an interpretation that reveals the peculiarities of managing purchase flows.

The first cluster – the cluster of typical flows – includes stores that can be recognized as the least problematic in terms of daily flow intensity. The daytime flow of customers is usually characterized by a greater spread of the time of their visit than the evening flow, the maximum intensity of which is observed in the early hours on average, against the shopping flows of the second cluster. As a result, a cluster of stores achieves the optimal uniformity of flows for the retail network, and it makes no sense to carry out peak pricing measures. This cluster mainly includes shops in Ivano-Frankivsk, located in residential areas, far from office centers.

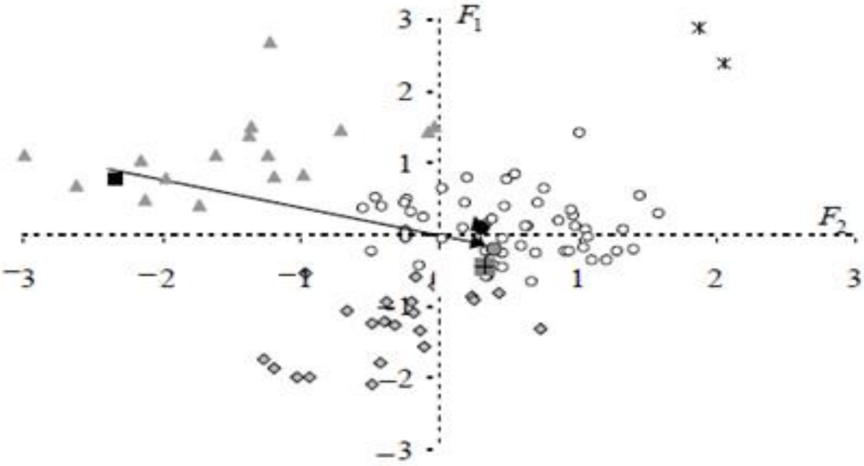

Fig. 4. Results of cluster analysis

Therefore, the only possibility to smooth out the daily intensity of the flow of customers may be to change the operating mode of the store, namely opening at an early hour. This would allow residents of the neighborhood to go to the store before work (from 7 to 8 o'clock) and buy, for example, lunches. In this way, it would be possible to stimulate the morning flow of customers and transfer the store into a three-flow cluster with the greatest uniformity of intensity throughout the day. The feasibility of such a measure should be additionally economically substantiated, which is beyond the scope of this study.

The second cluster - a cluster of convergent flows - covers mainly Ivano-Frankivsk stores located near administrative buildings, therefore the daytime flow of customers has the highest intensity at lunchtime, but the spread of the time of their visits is higher than that of the evening flow. As a result, due to the small difference between daytime and evening peak hours, there is a significant unevenness in the daily intensity of the flow of customers, which can be smoothed out by applying peak pricing. At the same time, both tactics of decreasing μ_1 and increasing μ_2 can be used . However, a decrease in μ_1 may negatively affect the difference in the spread of the time of day of store visits and the share k_1 of the daily flow of customers in the total flow (see Fig. 3), i.e., a multidirectional effect will occur. While an increase in μ_2 causes an increase in the dispersion of the visit time in the morning, thereby unambiguously increasing the uniformity of the daily intensity of the flow. The uncertainty of the result of eliminating the morning peak hour earlier gives rise to the need to study the final effect of peak pricing measures, which involve stimulating attendance in the morning, for example by establishing discounts.

The third cluster - the cluster of daytime concentration - contains retail outlets, the main problem of which purchase flows is their high concentration in the area of the daytime peak hour compared to the evening. As a result, the $\Delta\sigma$ indicator on average for all days of the week is 1.8 hours lower than in the retail network as a whole. Almost all points (91%) are located outside Ivano-Frankivsk. Therefore, it can be assumed that rural areas and small towns are characterized by a more uniform attendance of shops in the evening than during the day. In order to smooth the overall flow during the day with the help of peak pricing tactics, it is necessary to set lower prices in the evening, thereby stimulating an increase in μ_2 and the associated increase in σ_1 (see Fig. 3). As a result, a double positive effect of moving the store in the space of factors F_1 and F_2 to the upper right area with the most uniform flow of customers should be achieved.

The fourth cluster - three-flow - stands out among other selected groups of stores in that the morning flow of customers is clearly marked with daytime and evening flows. At the same time, the morning rush hour falls almost on the first hours of store opening. This is explained by the location of the two stores included in the cluster, near major transport intersections and in the administrative center. Consumers can visit such stores before the start of the working day.

As a result, the largest difference between the morning and evening peak hours is achieved throughout the retail network, which generates a more even flow of customers. However, in this case, the correct analysis requires the identification of model (1) at n = 3, which increases the number of parameters, and also requires modification of the dispersion formula (4) taking into account the three-component mixture.

A similar map (see Fig. 4), which displays the cluster structure of purchase flows of the trade network, can be used to track changes in the parameters of their intensity over time, in particular under the influence of peak pricing measures. However, taking into account the seasonal fluctuations characteristic of daily rhythms, it is necessary to display seasonally smoothed data on the maps of the cluster structure of flows. Unfortunately, due to the lack of information on sales in all stores of the retail network for a long period, the given map (see Fig. 4) is built as of October without removing seasonal effects. Nevertheless, if we trace the selected fluctuations of the estimates of the parameters of the intensity model (see Fig. 2), it is clearly visible that the values in October and March are quite comparable. Therefore, the map (see Fig. 4) will also correctly reflect the position of purchase flows in March.

We will analyze the effectiveness of purchasing flow management. The proposed flow intensity management efficiency criteria (Δμ, Δσ) were used to analyze the consequences of using peak pricing tactics in the considered retail outlet, where customers were given a discount in the morning. According to the results of such an action, it was expected to reduce the load on service personnel in the evening hours due to a more uniform intensity of the purchase flow during the day.

The analysis of the trends of changes in the estimations of the parameters of the intensity model for the entire analyzed period revealed a decreasing trend on weekdays both in the dynamics of $\hat{\mu}_1$and $\hat{\sigma}_1$(see Tab. 1). There is no clearly defined direction for the change in other estimates.

Therefore, under the influence of the action, a significant increase in Δμ and a decrease in Δσ were found. This multi-directional impact of such peak pricing tactics. The final effect is manifested in a change in the total variance of the time of day of visiting the store, which is estimated from relation (4) by replacing the parameters of the intensity model with their estimates. During the period from March (before the promotion) to October 2023 (four months after the promotion), the variance on average on weekdays increased by 15%. During peak pricing events from January 2023 to October 2023, the weekday variance remained at the previous level. Thus, we can confidently talk about the effectiveness of peak pricing measures to smooth out the uneven flow of customers of a retail trade enterprise. At the same time, the main effect is achieved in a fairly short period of time (up to six months), later, if stimulation is maintained, the situation stabilizes.

Conclusions about the effectiveness of the analyzed measures could also be made on the basis of a selective assessment of the variance of the time of day of shopping in the store, thereby not resorting to the identification of the intensity model (1). However, the proposed approach has the advantage that it reveals the mechanisms of influence of measures to regulate the intensity of flows due to the inclusion in the analysis of the characteristics of fashion and the spread of time of visiting the store by buyers of various structural components of the flow. In this case, the final positive result is achieved due to the growth of Δμ, which has a predominant effect and compensates for the negative effect of the decrease in Δσ.

Due to the peak pricing measures, in the short term from March to October 2023, daytime peak hours on weekdays decreased by 11% on average. At the same time, the indicator of the dispersion of the time of purchase by customers of the daily stream fell by as much as 27%. In the evening, the discount was practically not affected in the morning. However, the variation in the time of purchase in the evening increased: the $\hat{\sigma}_2$average value on weekdays increased by 8%. This can be explained by the negative correlation between parameter estimates revealed on the spatial data (see Fig. 3). In addition, in the long-term plan, in March 2023, compared to the same month of the previous year, the value $\hat{\sigma}_2$increases on average on weekdays by 16%, while the decrease $\hat{\mu}_1$remains $\hat{\sigma}_1$approximately at the same level - 12 and 30%, respectively. Thus, the relationship between the characteristics of daytime and evening flows has been confirmed, and the establishment of more favorable trading conditions for buyers of the daytime flow has a positive effect on the evenness of the evening flow.

For a visual display of the described results, we will use the already constructed card of the cluster structure of purchase flows (see Fig. 4). The values of F_1 and F_2 plotted on the map are calculated based on the found factor decomposition coefficients (see Tab. 2). The strongest effect of peak pricing is manifested in the first four months of the promotion. It should be noted that the analyzed trading point moves from the problematic cluster of convergent flows to the cluster of typical flows. Subsequently, some fluctuations occur mainly along the axis of the first factor, which indicates a change in the time of day of visiting the store. Moreover, in the long-term plan, in October 2023, compared to the same month of the previous year, a positive trend from the point of view of flow uniformity is manifested: the difference in the variation of the time of visit by day and evening flow $\Delta\sigma$ is increasing. Therefore, the map of the cluster structure of flows not only adequately reflects the dynamics of the overall uniformity of daily flows of customers, but also allows you to trace the influence of these dynamics of various components (F_1 and F_2), and even determine the current position of the store in relation to the clusters of the retail network.

5. CONCLUSIONS

As a conclusion, we can give a number of recommendations for the management of trading companies that plan to use peak pricing tactics when managing the intensity of purchasing flows. It is important to take into account the relationship between the characteristics of the structural components of the flow: one of the components (for example, the daytime flow) leads to a change in the intensity of the other (evening flow).

Stimulating visits in the early hours, in particular through the provision of morning discounts, is effective from the point of view of smoothing the daily intensity of the flow of customers of stores included in the cluster of convergent flows. At the same time, in the short term, a significant shift in the daytime peak hour should be expected, and in the long term, the evening flow becomes more uniform.

By providing more favorable shopping conditions in the evening in stores from the daytime concentration cluster, a general increase in the uniformity of the flow of customers is predicted.

The final effect should be justified by the economic benefit, which is achieved not only due to the equalization of the intensity of the buying flow during the day, but also due to the increase in the volume of sales, which compensates for the reduction of the mark-up in periods of low buying activity. Therefore, along with the relative intensity, it is necessary to investigate changes in the power of the flow and its qualitative composition according to the average purchase volume. In general, the proposed statement of the task of flow management and the model of its intensity are also applicable in the activities of companies of other types of economic activity that face the problem of peak demand, for example, in the power industry. This opens up opportunities to identify new patterns in consumer behavior.

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Розглянуто підхід до управління потоками покупців, який враховує як критерій ефективності, так і рівномірність добової інтенсивності. Для оцінки ступеня рівномірності запропоновано модель інтенсивності. Введено нову постановку завдання управління потоками покупців, основною рисою якої виступає критерій ефективності управління, заснований не на економічному ефекті, а на рівномірності потоку. При цьому час здійснення покупки, як правило, є випадковою величиною. Тоді співвідношення миттєвої інтенсивності потоку та його потужності на добу є ймовірністю відвідування магазину у певний момент часу. Вказану таким чином відносну інтенсивність можна досліджувати за допомогою функції щільності розподілу часу покупки. Для оцінки рівномірності пропонується переходити до моделі добової інтенсивності потоку. Побудована карта кластерної структури потоків дозволяє наочно аналізувати ефективність управління інтенсивністю потоків клієнтів, зокрема, у ході заходів пікового ціноутворення. Економічний ефект обгрунтований економічною вигодою, що досягається не тільки завдяки вирівнюванню інтенсивності купівельного потоку протягом доби, але й за рахунок зростання обсягу продажу, що компенсує зниження націнки у періоди низької купівельної активності. Тому, поряд із відносною інтенсивністю досліджено і зміни у потужності потоку та його якісному складі за середнім обсягом купівлі. Метою дослідження є оцінка ефективності заходів пікового ціноутворення з погляду згладжування добових коливань інтенсивності потоку покупців у торгових мережах. Для досягнення поставленої мети введено

нову постановку завдання управління потоками покупців, основною рисою якої виступає критерій ефективності управління, заснований не на економічному ефекті, а на рівномірності потоку. Для оцінки такої рівномірності пропонується переходити до моделі добової інтенсивності потоку. Важливо враховувати взаємозв'язок між характеристиками структурних складових потоку з кожною з компонент, як можуть вплинути на зміну інтенсивності. Загалом запропонована постановка завдання управління потоком і модель його інтенсивності застосовні й у діяльності компаній інших видів економічної діяльності, які стикаються з проблемою пікового попиту, наприклад, в електроенергетиці. Це відкриває можливості виявлення нових закономірностей у поведінці споживачів.

Ключові слова: купівельний потік, модель, інтенсивність, торгівля, покупка, ціноутворення.