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FORECASTING OF ACTUAL SALES QUANTITY OF A TRADING COMPANY

The database of a trading company has been analyzed to evaluate the influence of seasonality on actual sales quantity. Conclusion has been made as to autoregressive nature of the data under examination.

Due to analysis of existing approaches to determining seasonality and their tailoring to peculiar features of a trading company, an advanced toolkit has been set forth to tackle the problem. An introduction of a modulo operation term substantially facilitates taking into account the impact of periodicity on actual sales quantity of a company.

Calculations have been done to evaluate the reliability of the model set forth. The model proved to be more accurate and reliable as compared to an ordinary autoregressive and moving average model.

Key words: seasonality, sales, forecast, model, method, autoregression, moving average, value, prediction, error, reliability, coefficient, advantage, enterprise.

Formulation of the problem. In the context of increasing competition, the issue of determining the seasonality indexes of sales become particularly relevant. The correct definition of future actual sales quantity enables a company to make the most of its own resources. In addition, the company acquires ability to avoid the void stockpiling of unsold products, which also increases the efficiency of company's performance. The stocks of goods are brought in line with demand, competitive advantages grow due to more complete and rapid satisfaction of consumers' needs.

Therefore, research on seasonality of sales is timely and relevant.

Analysis of recent research and publications. In present conditions, the definition of seasonal indexes, as a rule, is based on the examination of «historical» databases, which consider the volume of consumption of goods (or its sales) as a function of time[1].

Plotting a trendline and its further adjustment with the help of seasonal factors is widely used to predict actual sales quantities[2]. The advantage of this approach is that due to the least squares method, the trend of changes (either growth or fall) is determined. The disadvantage of this approach is that when determining the seasonal indices for a given period (month, quarter, etc.), the value of an analyzed parameter is taken at the corresponding periods of previous cycles, so, the intensity of the changes of parameters and periodicity are missed.

In general, a toolkit dealing with time series is widely used to predict seasonality.

Moving average method should be mentioned as historically most widely applied method for determining seasonal indexes.

The advantage of the moving average lies in its relative flexibility (as compared to least squares method). However, the moving average in equal shares takes into account the influence of a few previous periods, while values of earlier periods of time either are taken into account to a lesser extent or are missed at all.

This discrepancy is partially eliminated by application of weighted moving average, when a Y_t parameter at the t-period is determined by formula

$$Y_t = \propto_{t-1} \times Y_{t-1} + \propto_{t-2} \times Y_{t-2} + \cdots + \propto_{t-k} \times Y_{t-k}, \quad (1)$$

where $Y_t, Y_{t-1}, \ldots Y_{t-k}$ –values of the parameter under examination at $t, t-1, t-k$ periods;

$\propto_{t-1}, \propto_{t-2}, \ldots \propto_{t-k}$ – weights that are determined from conditions

$$\sum_{i=t-1}^{t-k} \propto_i = 1, \quad (2)$$

To determine coefficients $\propto_{t-1}, \propto_{t-2}, \ldots \propto_{t-k}$ while plotting time series, equation

$$\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \to min \quad (3)$$

must be solved.

Function $\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$ defines the square of errors and is denoted as SSE.

To find the coefficients satisfying Conditions (3), generalized reduced gradient method (GRG) is being applied.

In addition to absolute indicators (sales), relative indicators (indexes, percentage) are widely used to assess seasonality, making it easier to visualize trends.

The nature of seasonality process (time cyclicity) facilitates the application of toolkits which involve the repetition of a phenomenon with a certain multiplicity in time. First of all, trigonometric functions (sinusoidal time dependence) and Fourier terms, represented by formulas (4) and (5) respectively, should be noted [3].

$$Y_i = a + bt + \propto \sin(2\pi\omega T_i + \Phi) + E_i \quad (4)$$

$$Y_i = a + bt + \sum_{k=1}^{k} \left(\propto_k \sin\left(\frac{2\pi kt}{m} + \Phi\right) + \beta_k cos\left(\frac{2\pi kt}{m} + \Phi\right)\right) + E_i \quad (5)$$

In both cases, the solution of problem is reduced to definition of constant coefficients (parameters $a, b, \propto, \propto_k, \beta_k$) satisfying Equation (3).

Moreover, attention should be noted to techniques which combines simultaneous application of moving average and auto-regressive approaches. Depending on completeness and nature of the coverage of variables being considered, ARMA (autoregressive moving average) [4], ARIMA (autoregressive integrated moving average) [5], SARIMA (seasonal autoregressive integrated moving average) [6] should be noted.

ARMA model, which depicts the primary concept of autoregressive concept, is as follows[4]

$$Y_i = c + \varepsilon_i + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \quad (6)$$

where c – a constant,

ε_t – a sequence of independent and identically normally distributed random variables, with zero mean;

$Y_t, \ldots, Y_{t-i}$ – real numbers;

α_i – autoregressive coefficients;

β_i –moving average coefficients.

The difference between seasonal models and cyclic patterns is that seasonality is usually associated with a fixed-time period, while cyclicity is due to changes in time without interconnection with a fixed period.

Among the models that determine seasonality with additive parameters, it is necessary to note Holt-Winters model [7] which takes into account the exponential trend and additive seasonality. Due to additivity, the formulation of cyclic impact on the value of a predicted parameter is substantially simplified. However, this techniques necessitates an enhanced database and is rather «sensitive» in its application.

Highlighting the previously unsettled issues and the formulation of the problem. As shows the analysis of publications on the problem of seasonality, the issue is sufficiently well considered and studied. Along with this, there are no practical recommendations in the literature on the use of certain methods depending on specifics of database and peculiar features of the enterprise. In this regard, the author considers it appropriate to formulate the main criteria for a toolkit being involved in assessing the impact of seasonality on sales of the company.

The model should be easy to use and provide reliable results. Moreover, it is uncontested that formulation of individual recommendations on its utilization will contribute to widespread the application of the model in determining seasonal indexes.

Formulating the goals of the article (task statement). The purpose of the paper is to assess the impact of seasonality on the sales of a trading company with substantiation of such a toolkit that thoroughly takes into account the features of initial database. In addition, statistical evaluation of the results is needed to confirm validity of the author's hypothesis as to application of the model selected. Recommendations on the limits of model's validity and peculiar features of its application will contribute to its scientific and practical value.

Presentation of the main research material with full substantiation of received scientific results. To solve the research problem, it is proposed to apply the approach provided by ARMA model (autoregressive + moving average). The primary sales information for four years (48 months) is shown in tab. 1.

Table 1

Sales over 4 years (48 months)

Month	Actual sales quantity	Month	Actual sales quantity	Month	Actual sales quantity
1	1037.84	17	643.43	33	803.28
2	995.73	18	637.06	34	938.11
3	895.43	19	661.19	35	1076.69
4	862.67	20	722.63	36	1087.02
5	618.48	21	742.95	37	1058.10
6	527.76	22	877.87	38	1160.25
7	803.75	23	1090.30	39	973.28
8	761.86	24	914.93	40	915.80
9	779.24	25	1078.07	41	661.92
10	783.83	26	983.89	42	719.90
11	1090.89	27	806.63	43	646.76
12	1168.02	28	842.98	44	696.17
13	1095.73	29	593.05	45	856.39
14	1038.25	30	701.70	46	846.25
15	903.01	31	665.02	47	1049.55
16	910.45	32	664.87	48	1104.51

In order to visualize the data in tab. 1, they are presented as a graph in fig. 1, from which a sales cycle is clearly traceable due to the seasonality of sales.

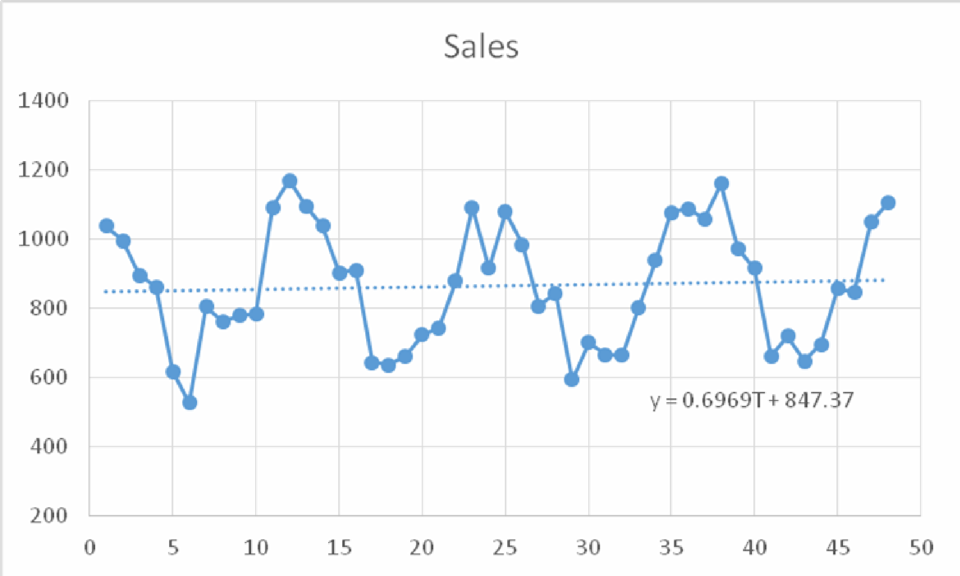

Fig. 1. Sales within 48 months

The mean of the population shown in tab. 1 equals $\bar{Y}$ = 864.45, the standard deviation σ = 177.48.

The trend line, shown in fig. 1, has the form

$$Y = 0.6969 \times T + 847.3, \quad (7)$$

Despite the obvious cyclicity in Figure 1, to prove (or refute) the validity of autoregressive approach we carry out Dickey-Fuller test to check our suggestion.

Applying usual linear regression techniques, due to t-coefficient failure to follow a bell-shape curve we cannot use the usual t test. The coefficient under investigation follows a tau distribution, so we have to determine whether the tau statistic τ is less than τ_{crit} based on a table of critical tau statistics shown in Dickey-Fuller Table.

As shown in [8], the set of data should be considered as a unit-root (stationary) system if the calculated tau exceeds the critical value. Among the three varieties of the Dickey-Fuller test, we choose Type Constant without Trend, which is described by the equation

$$\Delta y_i = \beta_0 + \beta_1 y_{i-1} + \varepsilon_i \quad (8)$$

The results of calculating tau statistics using the linear regression approach are given in tab. 2.

For statistical data evaluation, we additionally apply the following criteria of ARMA(p,q) function.

Aikike's Informational Criterion (AIC)

$$AIC = nLN\left(\frac{SSE}{n}\right) + 2k \quad (9)$$

Bayesian Information Criteria (BIC)

$$BIC = nLN\left(\frac{SSE}{n}\right) + kLN(n), \quad (10)$$

in our case (a constant term included)

$$k = p + q + 2, \quad (11)$$

where p is the order of the autoregressive part and q is the order of the moving average part.

The output of regression analysis is shown in tab. 2.

Table 2

Output of regression analysis

Regression Analysis						
OVERALL FIT						
Multiple R	*0.379012*		*AIC*	*448.7891*		
R Square	*0.14365*		*AICc*	*449.3605*		
Adjusted R Square	*0.124188*		*BIC*	*452.4464*		
Standard Error	*128.6236*					
Observations	*46*					
	ANOVA			*Alpha*	*0.05*	
	df	*SS*	*MS*	*F*	*p-value*	*sig*
Regression	*1*	*122109.2*	*122109.2*	*7.380867*	*0.009389*	*yes*
Residual	*44*	*727936.8*	*16544.02*			
Total	*45*	*850046*				
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*
Intercept	*260.943*	*97.04932*	*2.688767*	*0.010091*	*65.35293*	*456.533*
Sales	*-0.30227*	*0.11126*	*-2.71678*	*0.009389*	*-0.5265*	*-0.07804*

Since $\tau_{crit} < 2.71678$, the time series under investigation should be considered as not stationary.

To confirm the validity of autoregressive approach, we plot a correlogram drawing upper and lower bounds (respectively B_{up} and B_{low}) for autocorrelation r_h with significance level $\propto = 0.05$ using equation

$$B = \pm z_{1-(1-\propto/2)} SE(r_h), \qquad (12)$$

Having found the autocorrelation function of each time period, we plot the correlogram shown at fig. 2.

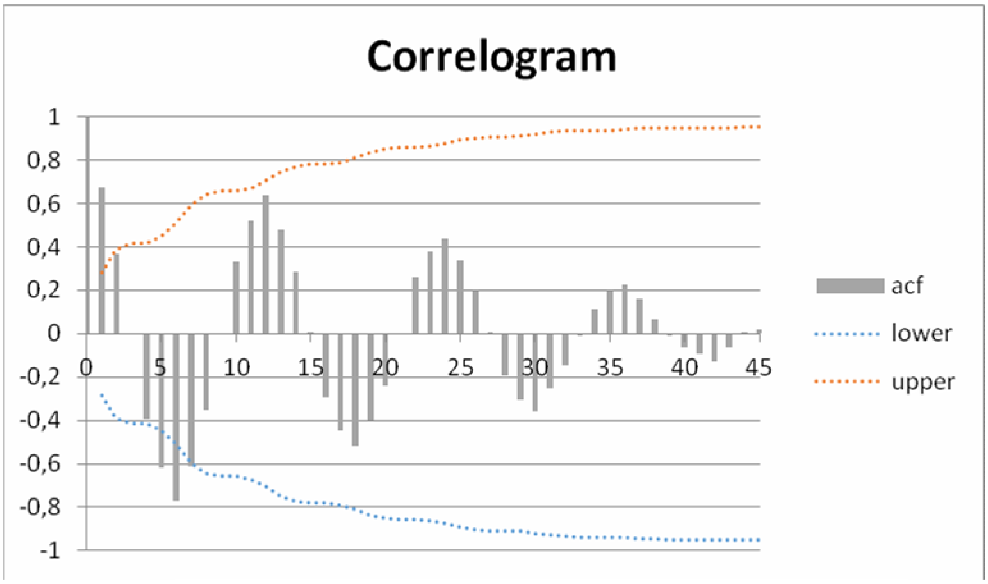

Fig. 2. Correlogram of the «historical database»

Data shown in fig. 2, refute the hypothesis of the randomness of the data array. Using equation (11) to determine the lower and the upper bounds for autocorrelation (significance level $\propto = 0.05$) of each value of the autocorrelation function. These

bounds are also shown in fig. 2

Since the autocorrelation functions are located within B_{up} and B_{low} boundaries, the function we are investigating should be defined as autoregressive.

To determine the equation that describes the time series, we use

$$y_i = \sum_{j=1}^{p} \Phi_j\, y_{i-j} + \varepsilon_i + \sum_{j=1}^{q} \theta_j\, \varepsilon_{i-j}, \qquad (13)$$

in which factors Φ_j and θ_j are being determined by criterion of the minimum sum of squares of errors

$$\sum_{i=1}^{p} \varepsilon_i^2 \to min \qquad (14)$$

The search for the coefficients Φ_j and θ_j satisfying (14) is being performed by an optimization process.

We present the autoregressive series ARMA (3,3) in the form of a correlation dependence

$$y_i = \Phi_0 + \sum_{j=1}^{p=3} \Phi_j\, y_{i-j} + \varepsilon_i + \sum_{j=1}^{q=3} \theta_j\, \varepsilon_{i-j} \qquad (15)$$

Statistics of calculations is shown in tab. 3.

Table 3

Statistics of ARMA (3,3)

Regression Analysis							
OVERALL FIT							
Multiple R	*0.9119*		*AIC*	*370.26*			
R Square	*0.8316*		*AICc*	*374.62*			
Adjusted R Square	*0.8027*		*SBC*	*382.42*			
Standard Error	*76.1223*						
Observations	*42*						
ANOVA				*Alpha*	*0.05*		
	df	*SS*	*MS*	*F*	*p-value*	*sig*	
Regression	*6*	*1001491.2*	*166915.2*	*28.81*	*3.68758E-12*	*yes*	
Residual	*35*	*202811.33*	*5794.61*				
Total	*41*	*1204302.59*					
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*vif*
Intercept	*-1098.11*	*246.5080*	*-4.4547*	*0.0000823*	*-1598.5510*	*-597.6755*	
Y_{i-1}	*3.5287*	*0.4940*	*7.1429*	*0.00000003*	*2.5258*	*4.5316*	*53.0231*
Y_{i-2}	*-1.5673*	*0.5268*	*-2.9751*	*0.0052791*	*-2.6368*	*-0.4978*	*61.0156*
Y_{i-3}	*0.3151*	*0.2923*	*1.0779*	*0.2884573*	*-0.2784*	*0.9086*	*18.7946*
ε_{i-1}	*-3.3990*	*0.5345*	*-6.3591*	*0.0000003*	*-4.4841*	*-2.3139*	*26.6529*
ε_{i-2}	*-0.8889*	*0.2770*	*-3.2087*	*0.0028518*	*-1.4513*	*-0.3265*	*7.4232*
ε_{i-3}	*-1.5275*	*0.2961*	*-5.1584*	*0.0000099*	*-2.1287*	*-0.9264*	*8.4239*

The statistics of tab. 3 indicate that the model is sufficiently reliable in determining the auto-regression dependence within the «historical» database.

However, its application in order to obtain predictive indicators is complicated due to the fact that to determine each consequent parameter Y_i we need to apply two «historical» parameters: Y_{i-1} and ε_{i-1}. We face the uncertainty of these two parameters already while determining the second predictive parameter running. This condition reduces the reliability of the model, and with each subsequent prognosis step the number of uncertain parameters doubles. Therefore, it is necessary to apply a more reliable model, in limits of which the number of uncertain parameters in predicting would be less. Moreover, to evaluate the accuracy of models, we suppose, that in compliance with conditions of comparability, the number of terms of the techniques we intend to formulate, should not exceed the number of terms in (15).

To achieve our aim, our steps should be as follows.

First, we need to reduce the number of uncertain parameters $(y_{i-j}, \varepsilon_{i-j})$ of equation (15) for each y_i.being predicted.

This can be achieved by simultaneously taking into account autoregressive nature of the model, the smoothing effect (moving average) in relation to periodicity of the process. The latter is being achieved by entering a function ***modulo*** term, which determines the periodicity of the process involving the remainder of division.

To facilitate the aim of our research, the author proposes to determine the value y_i, which is defined within i-th period of the cycle by formula

$$\hat{y}_i = \Phi_0 + \sum_{j=1}^{p} \Phi_{i-j} \times y_{i-j} \times (T_c \; mod \; T_{i-j}) \tag{16}$$

The actual value y_i is related to the predicted value of $\hat{y}_i$by equation (17) applying the *i*-period error

$$y_i = \hat{y}_i + \varepsilon_i, \tag{17}$$

Combining equations (16) and (17) we obtain equation (18), which we use to identify unknown $\Phi_0, \Phi_{i-j}, \dots \Phi_{i-p}$

$$y_i = \Phi_0 + \sum_{j=1}^{p} \Phi_{i-j} \times y_{i-j} \times (T_c \; mod \; T_{i-j}) + \varepsilon_i \tag{18}$$

The coefficients $\Phi_0, \Phi_{i-j}, \dots \Phi_{i-p}$ are being calculated by solution of a multiple linear regression equation.

The results of the calculation applying the author's model are shown shown in tab. 4.

Applying data in Table (4), we formulate the time series equation of y_i as

$$y_i = 428.6336 + 0.0038y_{i-1} + 0.0274y_{i-2} + 0.0134y_{i-3} + 0.0242y_{i-4} + 0.0146y_{i-5} + 0.0134y_{i-6} + \varepsilon_i \quad , \tag{19}$$

Table 4

Statistics of the author's model

Regression Analysis							
OVERALL FIT							
Multiple R	*0.919547*		*AIC*	*366.6217*			
R Square	*0.845566*		*AICc*	*370.9853*			
Adjusted R Square	*0.819091*		*BIC*	*378.7854*			
Standard Error	*72.8963*						
Observations	*42*						
ANOVA				*Alpha*	*0.05*		
	df	*SS*	*MS*	*F*	*p-value*	*sig*	
Regression	*6*	*1018317*	*169719.5*	*31.93896*	*8.36E-13*	*yes*	
Residual	*35*	*185985.5*	*5313.871*				
Total	*41*	*1204303*					
	coeff	*std err*	*t stat*	*p-value*	*lower*	*upper*	*vif*
Intercept	*428.6336*	*39.18227*	*10.93948*	*7.68E-13*	*349.0893*	*508.1778*	
y_{i-1}	*0.003809*	*0.004064*	*0.937409*	*0.354972*	*-0.00444*	*0.012059*	*1.245117*
y_{i-2}	*0.02742*	*0.004299*	*6.377681*	*2.46E-07*	*0.018692*	*0.036148*	*1.355967*
y_{i-3}	*0.013429*	*0.004297*	*3.125196*	*0.003562*	*0.004705*	*0.022152*	*1.338448*
y_{i-4}	*0.024199*	*0.004276*	*5.659044*	*2.17E-06*	*0.015518*	*0.03288*	*1.348849*
y_{i-5}	*0.01456*	*0.004283*	*3.399157*	*0.001702*	*0.005864*	*0.023256*	*1.398854*
y_{i-6}	*0.013433*	*0.003897*	*3.447235*	*0.001491*	*0.005522*	*0.021344*	*1.279163*

Using equation (19), we determine y_i for 49-60 months (next two years). For the interval $i > 48$, due to the unknown values of ε_i, we accept $y_i = \hat{y}_i$. It should be noted, that unlike equation (15) with at least two unknown parameters ($\varepsilon_i, \varepsilon_{i-1}$), each equation of $\hat{y}_i$ we use contains only one unknown parameter (ε_i).

As an alternative to suggestion $y_i = \hat{y}_i$, we can apply Monte Cristo method to simulate ε_i under a classic Bell-shaped curve (normal distribution).

The results of comparison with «historical» database statistics are shown in fig. 3.

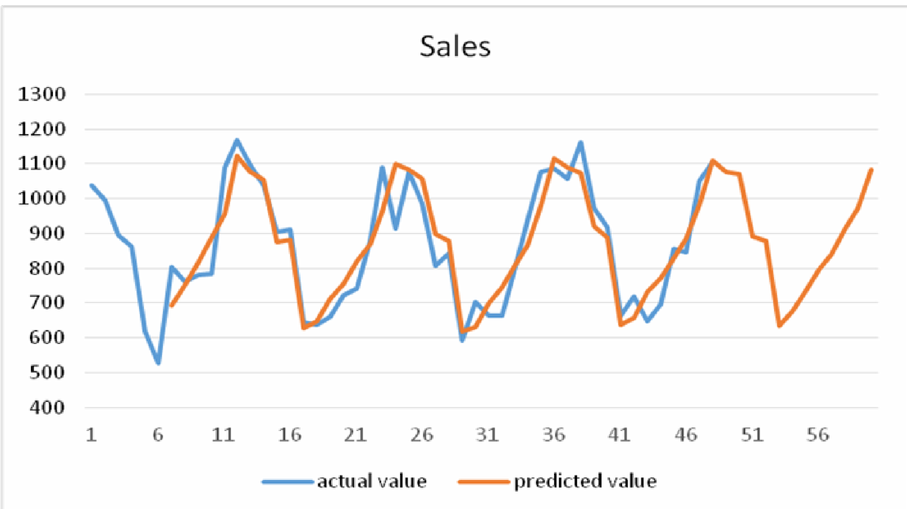

Fig. 3. Results of calculation

The trend line of the predicted data array is described by equation

$$Y = 0.3819 \times T + 859.73 \qquad (20)$$

Analyzing (7) and (20), one can conclude that in (20) there is a tendency to maintain an average sales growth rate and a slight decrease of its intensity.

Tab. 5 shows the statistics of calculations performed with application of the author's model and classic ARMA (p =3, q=3) model.

Table 5

Comparison of statistics

Coefficient / criterion	*Author's model*	*ARMA (p =3, q=3)*	*Preferable level of indicator*
Multiple R	***0.9195***	*0.9119*	*high*
R Square	***0.8456***	*0.8316*	*high*
Adjusted R Square	***0.8191***	*0.8027*	*high*
Standard Error	***72.8963***	*76.1223*	*low*
Observations	*42*	*42*	
AIC	***366.62***	*370.26*	*low*
AICc	***370.99***	*374.62*	*low*
BIC	***378.79***	*382.42*	*low*

As evidenced by tab. 4, application of the author's techniques (an autoregressive approach with introduction of a ***modulo operation*** term to take into account the periodicity of sales) has yielded reliable and more accurate results in comparison with a classic ARMA model.

Conclusions and suggestions. The database of a real trading company regarding the seasonality of sales was analyzed. Using the Dickey-Fuller test and plotting a correlogram, a conclusion has been made as to autoregressive nature of the data under examination.

Due to analysis of approaches to determining seasonality, an advanced toolkit has been set forth. It enables us to take into account the seasonality influence on the sales of a trading company.

The author's approaches is based on ARMA (p,q) techniques. To enhance the reliability of the model due to periodicity of sales, we introduce a modulo operation term. In comparison with traditional ARMA (p,q) model, our model yields more reliable and accurate results while plotting a multilinear correlation functions basing on «historical» data array. As to forecasting of actual sales quantity, the model we set forth in this article is more preferable due to the following fact. To apply our toolkit we need to determine (or stimulate) only one parameter (ε_i), while existing ARMA (p,q) techniques involves at least two unknown parameters ($\varepsilon_i, \varepsilon_{i-1}$).

As an alternative to suggestion $y_i = \hat{y}_i$ we use while forecasting y_i (i.e. $\varepsilon_i = 0$), the simulation under a traditional bell-shaped curve involving Monte Cristo method can be applied. However, the application of author's techniques provides a model with a lower level of uncertainty as compared to ARMA (p,q).

As further research topic, the author outlines the further investigation of issues of relationship between scope of information, the pace of the average moving and duration of cycle. In addition, the simulation of predicted errors using different stochastic methods will increase the reliability of the approach we set above.

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Прогнозування обсягів продаж торгівельної компанії

Проаналізовано базу даних торгівельної компанії в контексті оцінки впливу сезонності на фактичний обсяг продажів. З використанням статистичного апарату зроблено висновок про авторегресивний характер даних, що досліджуються. На підставі аналізу існуючих підходів до визначення сезонності та їх адаптації до особливостей торгівельної компанії розроблено вдосконалений інструментарій для вирішення завдання. Введення операції ділення по модулю в функцію визначення сезонних обсягів продажів суттєво полегшило облік впливу періодичності на авторегресивний характер сезонності. Для оцінки надійності запропонованої моделі здійснено її статистична апробація і порівняння з аналогічними показниками базової моделі. Підтверджено більш високу надійність розробленої моделі в порівнянні зі звичайною моделлю авторегресії і ковзної середньої.

Ключові слова: сезонність, продаж, прогноз, модель, метод, авторегресія, ковзаючи середня, показник, надійність, прогнозування, посилка, коефіцієнт, перевага, підприємство.

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Прогнозирование объемов продаж торговой компании

Проанализирована база данных торговой компании в контексте оценки влияния сезонности на фактический объем продаж. С использованием статистического аппарата сделан вывод о авторегрессивном характере исследуемых данных. На основании анализа существующих подходов к определению сезонности и их адаптации к особенностям торговой компании разработан усовершенствованный инструментарий для решения задачи. Введение операции деления по модулю в функцию определения сезонных объемов продаж существенно облегчило учет влияния периодичности на авторегрессивный характер сезонности. Для оценки надежности предложенной модели осуществлена ее статистическая апробация и сравнение с аналогичными показателями базовой модели. Подтверждена более высокая надежность разработанной модели в сравнении с обычной моделью авторегрессии и скользящей средней.

Ключевые слова: сезонность, продажи, прогноз, модель, метод, авторегрессия, скользящая средняя, показатель, надежность, прогнозирование, ошибка, коэффициент, преимущество, предприятие.