https://doi.org/10.23934/2223-9022-2019-8-3-246-256

Selection of Prediction Method of Basic Statistical Work Parameters of N.V. Sklifosovsky Research Institute for Emergency Medicine of the Moscow Healthcare Department

B.L. Kurilin*, V.Y. Kisselevskaya-Babinina, N.A. Karasyov, I.V. Kisselevskaya-Babinina, E.V. Kislukhkina, V.A. Vasilyev

Laboratory for Organization of Inpatient Care
N.V. Sklifosovsky Research Institute for Emergency Medicine of the Moscow Healthcare Department
3 Bolshaya Sukharevskaya Square, Moscow 129090, Russian Federation

*** Contacts:** Boris L. Kurilin, Researcher of the Laboratory for Organization of Inpatient Care, N.V. Sklifosovsky Research Institute for Emergency Medicine of the Moscow Healtcare Department. Email: kbl11@yandex.ru

BACKGROUND The most important part of the state social and economic policy is optimization of the healthcare system, where the loss of public health leads to economic damage. Against this background, forecasting the work of medical institutions is the basis for the successful development of healthcare, despite the fact that the healthcare system, indicators and standards of medical and social welfare are still not stable, and a clear development strategy for the short- and long-term period has not been worked out.
AIM OF STUDY Determining the most optimal method for predicting the work of a medical institution, based on identification of the main trends in the time series when constructing a model of the dependence of parameters or determining the behavior of data as a stochastic series (i.e. modeling random processes and random events with some random error).
MATERIAL AND METHODS To predict the main statistical indicators of N.V. Sklifosovsky Research Institute for Emergency Medicine based on a retrospective analysis, data were used that were submitted to the City Bureau of Medical Statistics and entered into official reporting forms (form № 30, approved by Goskomstat of the Russian Federation dated September 10, 2002, № 175): the number of hospitalized patients and mortality rates in inpatient and intensive care units.
To select the optimal methodology for the experimental forecast model, data were used for the period from 1991 to 2016. Indicators for 2017 were taken as control values.
RESULTS As a result of the comparison of several methods (moving averages, least squares approach, Brown model, Holt–Winters method, autocorrelation model, Box–Jenkins method) as applied to the work of N.V. Sklifosovsky Research Institute for Emergency Medicine, the Holt–Winters model was chosen as the most appropriate one for the data characteristics.
FINDINGS 1. When using methods of moving averages, least squares, Box-Jenkins, as well as Brown model and autocorrelation, the forecast result is not always influenced by strictly straight-line indicators of the time series, due to the heterogeneity of the time series and the presence of outliers (often found in a medical institution providing emergency care), which lead to a significant decrease in the reliability of forecasting.
2. The application of the Holt–Winters model, which takes into account the exponential trend (the trend of time series indicators) and additive season (periodic fluctuations observed in the time series), is most suitable for processing statistical data and forecasting for long-term, medium-term and short-term periods taking the specifics of a hospital providing emergency care into account.
3. The choice of the optimal method for predicting the work of a medical institution, based on the identification of the main trends in the time series, taking most of the features in the modeling of random processes and events into account, allowed to reduce the relative forecast error.
Keywords: forecasting, alignment of time series, assessment of the reliability of differences in indicators
For citation Kurilin BL, Kisselevskaya-Babinina VY, Karasyov NA, Kisselevskaya-Babinina IV, Kislukhkina EV, Vasilyev VA. Selection of Prediction Method of Basic Statistical Work Parameters of N.V. Sklifosovsky Research Institute for Emergency Medicine of the Moscow Healthcare Department. *Russian Sklifosovsky Journal of Emergency Medical Care.* 2019;8(3):246–256. https://doi.org/10.23934/2223-9022-2019-8-3-246-256 (in Russ.)
Conflict of interest Authors declare lack of the conflicts of interests
Acknowledgments The study had no sponsorship
Affiliations

Boris L. Kurilin	Researcher of the Laboratory for Organization of Inpatient Emergency Care, N.V. Sklifosovsky Research Institute For Emergency Medicine, https://orcid.org/0000-0003-3019-1947
Victoria Y. Kisselevskaya-Babinina	Engineer of the Laboratory of Automated Control Systems, N.V. Sklifosovsky Research Institute for Emergency Medicine, https://orcid.org/0000-0002-9057-2162
Nikolay A. Karasev	Head of the Laboratory for Organization of Inpatient Emergency Care, N.V. Sklifosovsky Research Institute for Emergency Medicine, https://orcid.org/0000-0001-8370-6145
Irina V. Kisselevskaya-Babinina	Engineer of the Laboratory of Automated Control Systems, N.V. Sklifosovsky Research Institute for Emergency Medicine, https://orcid.org/0000-0003-4474-4469
Evgeniya V. Kislukhina	Researcher of the Laboratory for Organization of Inpatient Emergency Care, N.V. Sklifosovsky Research Institute for Emergency Medicine, https://orcid.org/0000-0002-8980-4931
Vladislav A. Vasilyev	Senior Researcher of the Laboratory for Organization of Inpatient Emergency Care, N.V. Sklifosovsky Research Institute for Emergency Medicine, https://orcid.org/0000-0003-3205-1243

AR — autoregressive model
ARIMA — autoreressive integrated moving average model
ARMA — autoregressive moving average model
MA — moving-average model

RELEVANCE

Forecasting the main statistical indicators of work in a medical institution providing emergency care is a complex of reasoned assumptions (expressed in qualitative and quantitative forms) regarding the structure of medical care in the future, which allows to predict events based on factors and trends for making appropriate administrative decisions correctly and fully, development of adequate preventive measures that will make it possible to avoid unwanted results in providing and medical care to patients. [1]

Since the forecast of the work of a medical institution is based on the probabilistic development of events, then, according to the Federal Laws (FL) dated July 20, 1995 N 115- FL "On State Forecasting and Socil and Economic Development Programs of the Russian Federation", Federal Law dated July 21, 2011 N 323- FL “On the Fundamentals of Protecting the Health of Citizens in the Russian Federation”, Federal Law dated November 29, 2010 N 326- FL “On Compulsory Medical Insurance in the Russian Federation”, depending on the tasks to build mathematical models in order to optimize the process of medical care as well as planning of various methods (including logistics and accounting for possible economic costs), exhaustive retrospective information is necessary based on statistical performance indicators for a significant (at least 10–12 years) observation period [2].

One of the promising directions for the development of forecasting is associated with adaptive methods. These methods allow you to build self-correcting models that can quickly respond to changing conditions [3]. Adaptive methods take into account the different informational value of the levels of the series and the "aging" of information. All this makes their use effective for forecasting unstable series with a changing trend. In adaptive methods, the different value of levels depending on their "freshness" can be taken into account using the system of weights attached to these levels.

Many of the basic forecasting methods are more likely to relate to individual techniques or procedures, others are packages of methods and differ from each other in the number of private techniques and/or the sequence of their application [4].

According to the degree of formalization, all forecasting methods are divided into intuitive and formalized (Fig. 1). Intuitive forecasting is used when the object is so complex that it is almost impossible to analytically take into account the influence of many factors. Formalized forecasts are built using methods of computational mathematics and allow you to get the most reliable data in a shorter time.

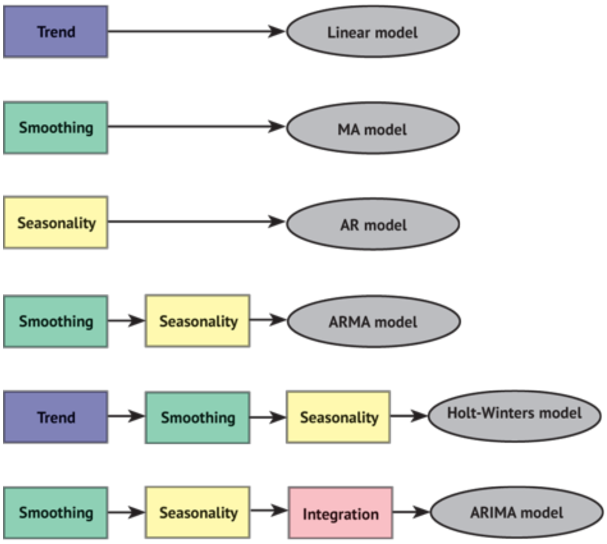

Fig. 1. The distribution of basic techniques and methods

Notes: AR — autoregressive model; ARIMA — autoregressive integrated moving average model; ARMA — autoregressive moving average model; MA — moving-average model

When choosing forecasting methods, an important indicator is the forecast forecast depth. Moreover, it is necessary not only to know the absolute value of this indicator, but also to attribute it to the duration of the evolutionary cycle of development of the forecasting object.

MATERIAL AND METHODS

For forecasting based on a retrospective analysis of the main statistical indicators of the N.V. Sklofosovsky Research Institute for Emergency Medicine for the period from 1991 to 2017, we used the data submitted to the City Bureau of Medical Statistics and entered into the official reporting forms (form N 30 approved by Goskomstat of the Russian Federation dated September 10, 2002, N 175): average day of work of a bed in a year, bed turnover, average bed-day, mortality rates in inpatient and intensive care units. To select the optimal methodology for the experimental forecast model, we used data from 1991 to 2016. In this case, the 2017 indicators were taken as reference values.

Several methods were selected based on the alignment of time series or the experimental forecast model of the main indicators characterizing the work of N.V. Sklofosovsky Research Institute for Emergency Medicine:

- moving average smoothing;
- least squares method;
- Brown model;
- Holt-Winters method ;
- autocorrelation model;
- Box-Jenkins method.

These methods were applied to data using the free software environment *R v*3.5.1 *(The R Project for Statistical Computing)*.

EVALUATION OF METHODS

When using forecasting methods, it is extremely important to evaluate the statistical significance of the resulting model and its forecast. These may be the coefficient of determination R^2, the Type I error *p-value* and the Akaike's criterion *AIC*.

The determination coefficient R^2 is calculated by the formula:

$$R^2 = 1 - \frac{\sigma^2 (y|x)}{\sigma^2 (y)},$$

where $\sigma^2 (y|x)$ is the conditional variance, $\sigma^2 (y)$ is the variance of the model data. The obtained value varies from 0 to 1 and is considered as the percentage of real data that describes the resulting model. Accordingly, in order to recognize the model as statistically significant, the coefficient of determination should not be lower than 0.5, and should exceed 0.8 for very good models.

The *p-value* actually means the probability of a hypothesis rejecting when it is correct, that is (in relation to forecast models) the probability of real data will deviate from the forecast in the future. The smaller the *p-value* , the more statistically significant the results. Traditionally, the *p-value* level is set to 5% or less. Based on a more accurate forecast, the level can be set from 0.5% or less.

The Akaike criterion was suggested as an alternative to the coefficient of determination.

$AIC = 2k - 2ln(L_{max})$,

where k is the number of model parameters, L_{max} is the maximum likelihood function of the model. The Akaike criterion cannot describe statistical significance itself and cannot be interpreted, however, in each specific case, it calculates its "relative weight" for each forecast; when comparing them, the prognosis is considered to be the best if for it the *AIC* value is the lowest.

For a more complete comparison, we will calculate these three estimates and compare different methods with their help.

LINEAR LEAST SQUARES METHOD

The time series for which the forecast is made is a set of values $\{y\}^n_{i=1}$ for several points $\{x\}^n_{i=1}$. The simplest prediction method is to assume that y has a formula dependence on x with unknown parameters α: $y_i = y\,\bar{y}(\alpha, x_i)$.

The basis of the least squares method is that the best approximation to real data is to minimize the sum of the squared differences between the actual level and the theoretical one:

$$\sum_i (y_i - \bar{y}(\alpha, x_i))^2 \to \min_{\alpha}. \qquad \text{(Formula 1)}$$

The least squares method is the main method for determining the parameters of various models and is often used in regression analysis and forecasting. In the future, we will refer to this method in the description of other forecasting models [5–8].

The type of the function $\bar{y}(\alpha, x)$ is selected using expert estimates, it can be a linear dependence, quadratic, exponential, etc. In the simplest case, a linear relationship is selected:

$\bar{y}_i(\alpha, x) = \alpha_1 x + \alpha_0$,

where $\bar{y}$ — aligned levels, α_0 — the initial level of the series; α_1 — the initial speed of the series; x — the time interval. Thus, its main trend is distinguished from the time series: for $\alpha_1<0$, the values decrease with increasing time x, and for $\alpha_1>0$ they increase.

In the general case, the coefficients α are calculated by the formulas:

$$\alpha_0 = \frac{\sum y_i}{n} - \frac{\alpha_1 \sum x_i}{n}, \qquad \alpha_1 = \frac{\sum y_i x_i - \frac{\sum x_i \sum y_i}{n}}{\sum x_i^2 - \frac{(\sum x_i)^2}{n}}.$$

Provided that the sum of the time intervals is zero ($\sum x_i=0$), the values α_0 and α_1 are calculated by the formulas:

$$\alpha_0 = \frac{\sum y_i}{n}, \qquad \alpha_1 = \frac{\sum y_i x_i}{\sum x_i^2},$$

where y are the levels of the series, n is the number of levels of the series.

The average predictive indicator is determined by continuing calculations of y_{theor}. Exactly y_{theor} of the next year is the average predictor ($y_{av\ pred}$). When calculating by the formula:

$y_{av\ pred} = y_{av} + (\alpha_1 x)$

The value x takes the next value with the same step as before (that is, 1 or 2 is added to the last value of x).

To determine the boundary values of the average predictive indicator, it is necessary to calculate its maximum and minimum values ($y_{max\ pred}$) and ($y_{min\ pred}$). To calculate $y_{max\ pred}$ and $y_{min\ pred}$ the values of $\sum \Delta+$ and $\sum \Delta-$ were used. Wherein:

$y_{max\ pred}$, where Δ_{av} is the average deviation up from the trend line, and n is the number of years above the trend line.

$y_{min\ pred}$, where Δ_{av} is the average deviation down from the trend line, and n is the number of years below the trend line.

To construct a linear dependence with respect to our data, we used the *lm* function from the standard *stats* package of the *R* program . The linear model allows you to see the trend line in the data clearly. Over 15 years, the total number of revenues and the number of admissions to intensive care has grown, while deaths and mortality have fallen. However, while in the case of total mortality and the number of deaths in a hospital, real data are in good agreement with the linear trend, then in the case of the number of admissions and the number of deaths, random outliers make prediction more difficult, and the reliability of the forecast is greatly reduced (Fig. 2).

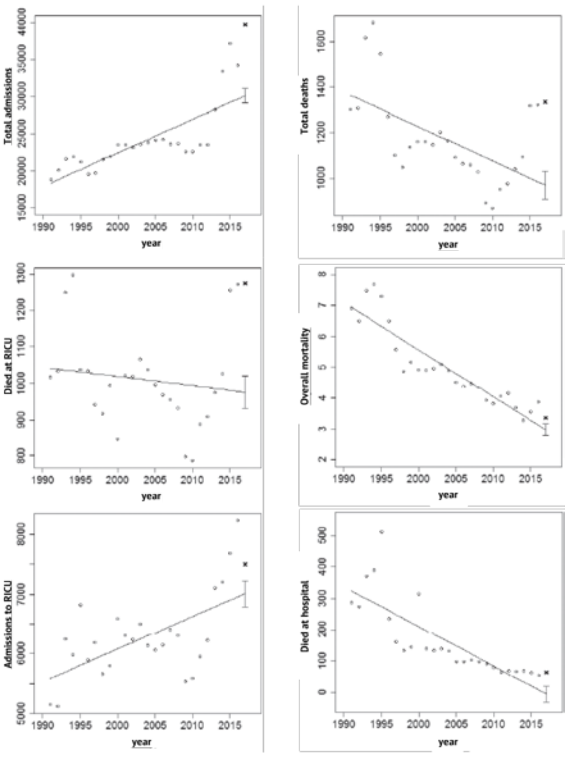

Fig. 2. Linear models for data on admissions, in-hospital deaths, intensive care deaths, general mortality, admission to intensive care, deaths in various departments. Dots show real data, crosses show values for 2017

Unfortunately, not a single real value for 2017 fell within the calculated boundary values, which is caused by overly sharp jumps. Confidence intervals are too large to indicate statistical significance of the forecast. The results of the evaluation of the models are given in table 1.

Table 1

Characteristics of linear models for each data set

Forecast value	R^2	AIC
Admitted totally	0.58	491.9
Died totally	0.29	345.6
Died in intensive care units	0.02	332.6
General mortality rate	0.83	44.2
Admitted to intensive care units	0.32	408.5
In-hospital deaths	0.63	301.0

As can be seen in Table 1, the best result was achieved for general mortality due to the large similarity of data behavior with the line. The number of admissions and the number of deaths in a hospital are described partially directly, since unsteady behavior is observed prior to 2000 for mortality and after 2010 for admissions. The most unreliable prognosis of the annual number of patients who died in intensive care, too high rises and unpredictable outliers prevent from constructing a line, and even the tendency for data to persistently decrease or rise remains in doubt.

Thus, the advantages of the least squares method of the linear model in relation to the work of a medical institution are the possibility of determining the development trend to increase or decrease with determination of its severity, but the forecast based on it has insufficient accuracy.

MOVING AVERAGE MODEL *(MA)*

This method works well if the data is the sum *q* of white noises:

$$y_t = \sum_{j=0}^{q} b_j \varepsilon_{t-j}, \qquad \text{(Formula 2)}$$

where *x* are terms of the series, *b* are the model parameters, and ε is white noise. That is, subsequent values of the time series accumulate errors of the previous ones.

The first-order equation can be rewritten in another way:

$$y_t = \varepsilon_t - \sum_{j=1}^{q} b_j y_{t-j}.$$

That is, each subsequent value is based on the previous ones, all with weights tending to zero.

The essence of the method is that the actual performance of the dynamic series is replaced by a theoreticalcally expected one by averaging two or three adjacent actual indices. Thus, a clear trend is seen. The larger the window, the greater the significance of the resulting trend, however, minor changes eliminate during the process.

Simple moving average is calculation using 2*n* points using the arithmetic mean:

$$\bar{y}_t = \frac{1}{2n} \sum_{i=t-n}^{t+n} y_i.$$

Weighted moving average is calculation using *n* points regarding higher and lower significance of individual values based on the arithmetic progression;

$$\bar{y}_t = \frac{2}{n(n+1)} \sum_{i=0}^{n-1} (n-i) y_{t-i}.$$

When calculating the moving average for all periods, the forecast is built for one period according to the formula:

$$y_{t+1} = m_{t-i} + \frac{1}{n}(y_t - y_{t-1}),$$

where $t + 1$ is the forecast period; *t* is the period preceding the forecast period (year, month, etc.); y_{t+1} is the predicted indicator; m_{t-1} is moving average for two periods before the forecast; *n* is the number of levels included in the smoothing interval; y_t is the actual value of the investigated phenomenon for the previous period; y_{t-1} is the actual value of the investigated phenomenon for two periods preceding the forecast.

To construct a moving average and its predicted values, the *ma* function from the *forecast* package of program *R* is used. Figure 3 shows the results of applying the moving average method for hospital statistics. The graphs show that this method gives good predictive estimates of data on total mortality and deaths in wards. However, the number of admissions and deaths in the hospital are predicted worse. Table 2 shows that the moving average method is more statistically significant in comparison with the linear least-squares method, since its determination coefficient is higher for all predicted values.

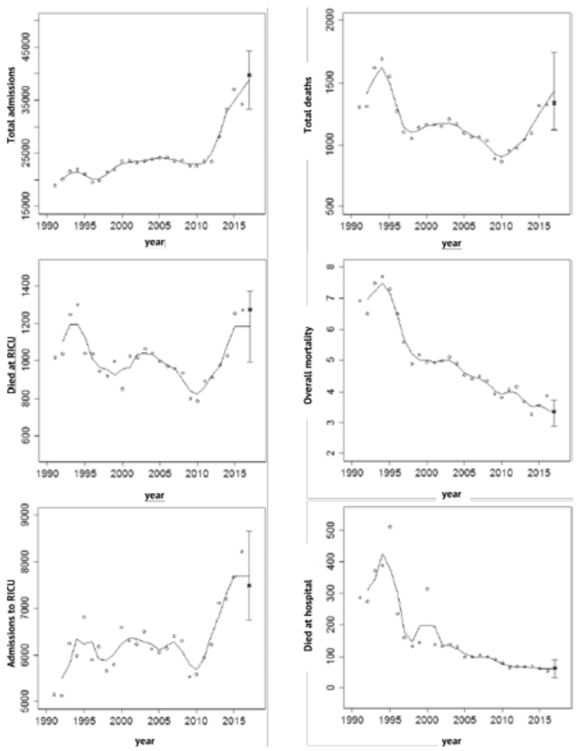

Fig. 3. Smoothing by the moving average for data on admissions, in-hospital deaths, intensive care deaths, general mortality, admission to intensive care, deaths in various departments. Dots show real data, crosses show values for 2017

Table 2

Characteristics of the moving average models for each data set

Forecast value	R^2	AIC
Admitted totally	0.96	402.4
Died totally	0.94	278.1
Died in intensive care units	0.94	274.7
General mortality rate	0.96	9.5
Admitted to intensive care units	0.95	349.6
In-hospital deaths	0.83	233.5

Admission to the intensive care unit and the number of deaths in intensive care units cannot be predicted with good accuracy due to the resulting difference in real and predicted values.

BROWN MODEL

In the Brown model, also known as the exponential smoothing method, the time series is smoothed using a weighted moving average, in which the values obey the exponential law.

The idea of the method is that the predicted value $\bar{y}_{t+1}$ is determined through the previous c predicted value $\bar{y}_t$, but adjusted with a certain coefficient by the deviation of the fact y_t from the forecast: $\bar{y}_{t+1} = \bar{y}_t + \alpha(y_t - \bar{y}_t)$. Quite often this model is presented as $\bar{y}_{t+1} = \alpha y_t + (1-\alpha)\bar{y}_t$. However, the meaning of the model does not change from this: it adapts to one degree or another (depending on the value of the coefficient α) to new incoming information.

The exponential smoothing method is similar to the moving average method. They have a common main principle that each point depends on the values of neighboring ones with some weights. The main differences of the Brown method is that the initial value is not affected and remains unchanged, as we move away from the initial data, the weights exponentially tend to zero, in addition, the data is smoothed not in the center, but in the nearest previous value.

In general, the Brown model can be applied in two cases:

- when it is necessary to smooth the existing data series to identify trends (usually in the case of stationary processes with a small error of each measurement), the value α is set in the range from 0 to 1;
- when a short-term forecast is needed. In this case, the best forecast result is obtained when α is set in the range from 0 to 2.

There is no standardized way to find the parameter α for all cases. Depending on the length of the smoothing interval *n*, the parameter is calculated as $\alpha = 2/(n+1)$. The optimal parameter can be obtained by minimizing the forecast errors with respect to α (formula 1).

Fig. 4 shows the results of forecasting statistics obtained as a result of applying the Brown model. In general, we can say that the model predicts data worse than a simple sliding window method. This can be explained by rapid changes in the considered indicators, to which the system was not able to respond.

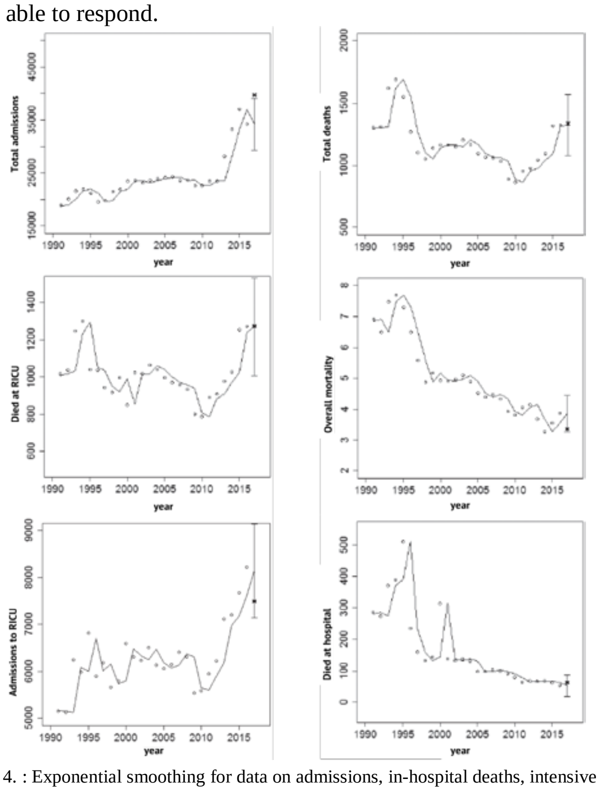

Fig. 4. : Exponential smoothing for data on admissions, in-hospital deaths, intensive care deaths, general mortality, admission to intensive care, deaths in various departments. Dots show real data, crosses show values for 2017

Table 3 shows that the coefficient of determination for all predicted values of the Brown model is lower than when using the moving average method.

Table 3

The Brown model characteristics for each data set

Forecast value	R^2	AIC
Admitted totally	0.93	474.9
Died totally	0.91	332.6
Died in intensive care units	0.89	330.3
General mortality rate	0.92	39.8
Admitted to intensive care units	0.49	412.6
In-hospital deaths	0.67	288.3

Since the changes in the predicted data are discontinuous, the Brown model gives statistically insignificant results.

HOLT–WINTERS METHOD

The Holt-Winters method is a modification of the exponential smoothing method for seasonal series. This method also takes into account the exponential trend (the trend of the time series) and additive seasonality (periodic fluctuations observed in the time series) [9, 10].

The model has two forms, depending on the seasonal component, either additive or multiplicative.

Let $y_0 \ldots y_t$, $y_i \in R$ be a time series. It is necessary to solve the problem of forecasting the time series:

$$\begin{cases} \bar{y}_{t+d} = (a_t + kr_t)\,\Theta_{t+k-s}, \\ a_t = \alpha \dfrac{y_t}{\Theta_{t-s}} + (1-\alpha)(a_{t-1} + r_{t-1}), \\ r_t = \gamma(a_t - a_{t-1}) + (1-\gamma) r_{t-1}, \\ \Theta_t = \beta \dfrac{y_t}{a_t} + (1-\beta)\,\Theta_{t-s}\ ; \end{cases}$$

$$\begin{cases} \bar{y}_{t+d} = a_t + kr_t\,\Theta_{t+k-s}, \\ a_t = \alpha(y_t - \Theta_{t-s}) + (1-\alpha)(a_{t-1} + r_{t-1}), \\ r_t = \gamma(a_t - a_{t-1}) + (1-\gamma) r_{t-1}, \\ \Theta_t = \beta \dfrac{y_t}{a_t} + (1-\beta)\,\Theta_{t-s}, \end{cases}$$

where s is the seasonality period, Θ_i, $i \in [0, s–1]$ is the seasonal profile, r_t is the trend parameter, a_t is the forecast parameter cleaned of the influence of trend and seasonality. Accordingly coefficient $\alpha \in [0, 1]$ indicates how much quantities depend on previous values, $\beta \in [0, 1]$ shows the importance of seasonality and $\gamma \in [0, 1]$ shows whether the data has pronounced clear trend.

It is suggested ti find optimal parameters α, β, γ experimentally.

To construct a model of Holt - Winters we use the Holt-Winters function of the standard package *stats* of R program and *forecast* package for its further prediction. Optimal parameters α, β, γ are found by minimizing the squared deviations (formula 1). However, the frequency of repetition of the values must be set manually, based on the type of data. To identify seasonality, it was suggested to draw up a graph of autocorrelation with a significant level of 0.4.

Figure 5 shows the graphs constructed for the studied indicators by the Holt-Winters method. It can be seen from them that, unlike the moving average method, the model did not smooth out the peaks and dips, but included them in the trend.

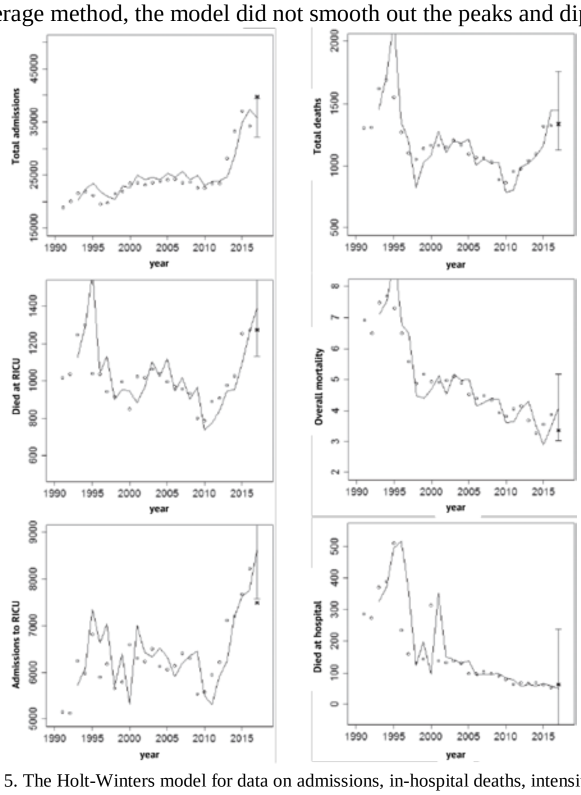

Fig. 5. The Holt-Winters model for data on admissions, in-hospital deaths, intensive care deaths, general mortality, admission to intensive care, deaths in various departments. Dots show real data, crosses show values for 2017

As can be seen from the Table 4, the Holt-Winters method allowed good results to be achieved. All random outliers (opening, closure of wards and intensive care units, overload or underload etc.) were smoothed out, but seasonal fluctuations remained, so the predicted values are closest to the real data.

Table 4

Characteristics of Holt-Winters models for each data set

Forecast value	R^2	AIC
Admitted totally	0.93	479.3
Died totally	0.89	343.5
Died in intensive care units	0.88	338.8
General mortality rate	0.91	46.8
Admitted to intensive care units	0.91	417.6
In-hospital deaths	0.68	294.6

AUTOREGRESSIVE MODEL *(AR)*

Using *AR* models, the seasonality of a time series is modeled. This model is built on the assumption that each member of the time series is formed with the help of *p* previous members, that is, the model has some data delay:

$$y_t = c + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t , \qquad \text{(Formula 3)}$$

where *y* are the members of the series, *c = const* is a constant level, *a* are the autoregression coefficients, ε_t is white noise.

Thus, the model already has a forecast for *p* steps forward with the available initial values $\{y_i\}$. The most rational way to determine the parameters of the autoregressive equation is to use the least squares method (formula 1).

However, the main task is to search for the order of autoregression *p*.

The results of applying the autoregressive model are shown in Fig. 6. Since modeling by this method provides for the preservation of previous periods, when predicting the total mortality and the number of deaths in a hospital, the model took into account the initial jumps in values and subsequently could not correctly display the decrease in these indicators.

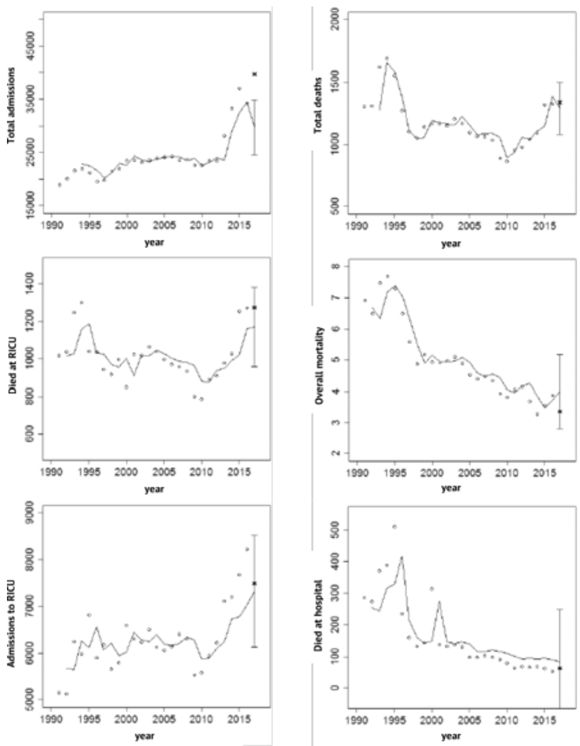

Fig. 6. Autoregressive model for data on admissions, in-hospital deaths, intensive care deaths, general mortality, admission to intensive care, deaths in various departments. Dots show real data, crosses show values for 2017

Table 5 shows that this model approximates the data worse than the Holt-Winters model.

Since our data have sharp changes in values, this forecasting method turned out to be unproductive. With a uniform number of admissions (until 2012), the model provided an adequate forecast, but with a sharp increase in the number of hospitalizations since 2012, the predicted data began to differ significantly from the real ones.

Table 5

Characteristics of autoregressive models for each data set

Forecast value	R^2	AIC
Admitted totally	2150786	464.22
Died totally	8744	319.5
Died in intensive care units	9491	318.55
General mortality rate	0.1532	35.61
Admitted to intensive care units	244620	403.5
In-hospital deaths	5919	306.48

AUTOREGRESSIVE MODEL - MOVING AVERAGE *(ARMA)*

As the name implies, this model is the sum of autoregression (formula 3) — data lag — and a sliding window (formula 2):

$$y_t = c + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t + \sum_{j=0}^{q} b_j \varepsilon_{t-j} .$$

Since we have already estimated the parameters *p* and *q* for the last two models, the same values were taken for calculations. The least squares method was used to estimate the coefficients of the independent variables of the model.

Fig. 7 and Table 6 show the results of forecasting the studied indicators using the *ARMA* model. This model is well suited for predicting data that stably maintains its dynamics over the entire considered time period. Since this condition is not fulfilled for our data, the values predicted by this method turned out to be different from the real ones.

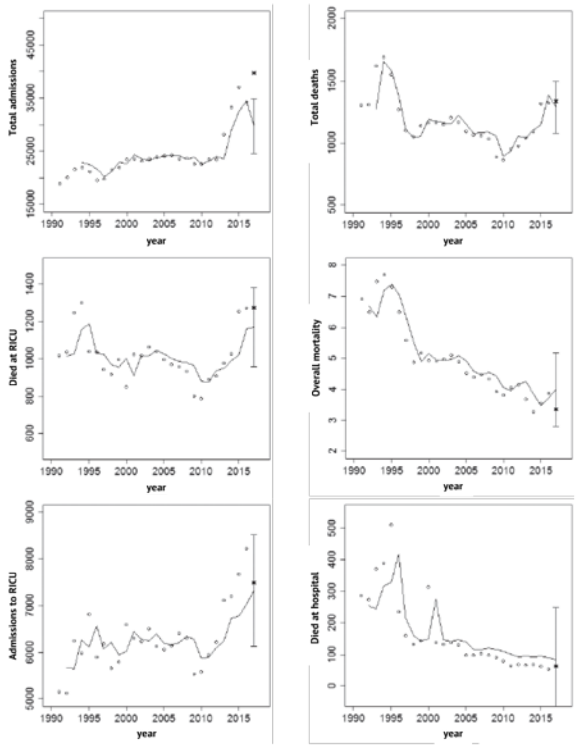

Fig. 7. The model of autoregression and moving average for data on admissions, in-hospital deaths, intensive care deaths, general mortality, admission to intensive care, deaths in various departments. Dots show real data, crosses show values for 2017

Table 6

Characteristics of autoregressive models for each data set

Forecast value	R^2	AIC
Admitted totally	1607957	466.84
Died totally	5606	319.61
Died in intensive care units	8142	321.59
General mortality rate	0.1331	38.96
Admitted to intensive care units	213385	406.43
In-hospital deaths	4553	308.57

The predicted values obtained by the *ARMA* method are worse than those obtained by the simple autoregressive method, since some of the real data has a large amplitude, which the model takes as the basis for further forecasting. This is clearly visible on the chart " Deceased in the Hospital."

BOX–JENKINS MODEL *(ARIMA)*

The so-called integrated model of autoregression — a moving average, an extended version of the *ARMA* model. *ARIMA* is based on the assumption that the data has autoregression (Formula 3), noise effect (Formula 2), and integration .

$$\Delta^d x_t = c + \sum_{i=1}^{p} \Delta^d x_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t .$$

Data integration implies the presence of a stable difference of some order. That is, $\Delta^d x_t = x_{t-d} - x_t \ \forall t$ retains its type and behavior.

The model is often used to predict time series and has many improvements and variations. The method is considered accurate enough to receive both short-term and long-term forecasts that do not require a separate assessment. However, to construct a model of the *ARIMA* type, a larger data set and their comprehensive analysis are required [11].

The model parameters are *p, d, q*, that is, the order of delay, the order of conservation of residuals, and the size of the sliding window.

The results of forecasting by the *ARIMA* method are shown in Fig. 8 and Table 7. According to the Table 7, this method turned out to be statistically weakly significant of all the above, since it provides at least 40 time points for forecasting. The graphs show that the simulated data differ a lot from the real ones.

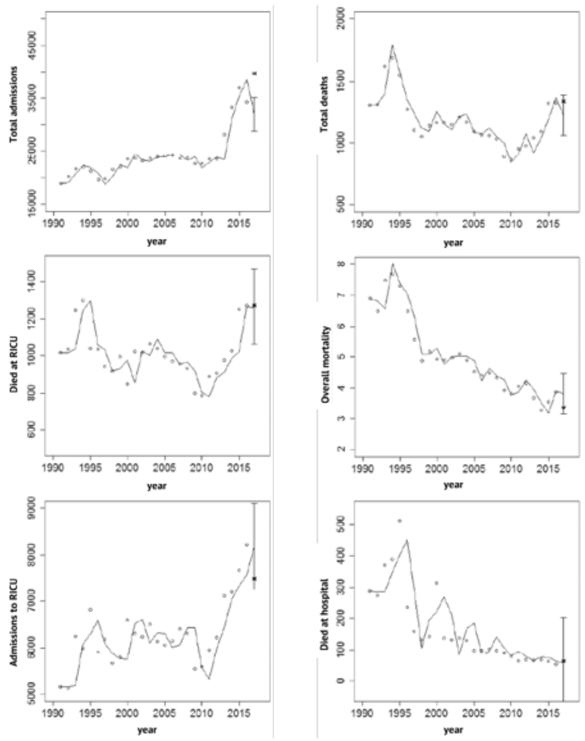

Fig. 8. The model of autoregression and moving average for data on admissions, in-hospital deaths, intensive care deaths, general mortality, admission to intensive care, deaths in various departments. Dots show real data, crosses show values for 2017

Table 7

Characteristics of autoregressive models for each data set

Forecast value	R^2	AIC
Admitted totally	1843255	446.71
Died totally	6893	306.98
Died in intensive care units	10767	313.15
General mortality rate	0.1069	31.31
Admitted to intensive care units	222159	389
In-hospital deaths	5466	296.82

Due to the small number of values analyzed, the use of the *ARIMA* method gave poor forecasting results, although it is considered a universal, reasonable and reliable forecasting method. In the future, we plan to apply it to a larger sample, breaking the data of each year quarterly.

RESULTS AND DISCUSSION

On the example of the study, we can state:

1. The **linear least-squares method** is applied only if you need to know the general long-term tendency of the series to increase or decrease. If the data has fluctuations, then the method will not be able to catch them. An important advantage of the least squares method is that it evens out data that had some calculation error, and the estimate obtained with its help is better than any other [12]. The method is used to solve data smoothing, interpolation and extrapolation problems.

Thus, the advantages of the least squares method of the linear model in relation to the work of a medical institution are in determining the development trend towards growth or decrease with the possibility of assessing its severity, but the forecast based on it has insufficient accuracy.

2. **The moving average method is** well adapted for evenly fluctuating data and can give good results even with uneven data. The sliding window is widely used for preliminary processing in other types of prediction and analysis, as it allows to exclude the influence of the random component. However, with strong jumps closer to the "future", it may fail. The disadvantage of this method is its locality. It does not respond to data in general and cannot predict a sharp change in data behavior, relying only on the nearest points [13].

3. **The Brown method** is suitable for data with a dependence on previous values and without strong amplitude fluctuations. Exponential smoothing is the most common method for predicting different time series. Its main advantages are rather simple calculations and the flexibility to describe different changes. The method of exponential smoothing allows you to get estimates of trend parameters that describe not the average level of the phenomenon, but the trend that has developed at the time of the last observation. For this method, it is very important to choose the smoothing parameters and the initial conditions. The forecasting method under consideration is quite effective and reliable. But it helps predict the process only in the short term, i.e. only 1-2 years ahead [14, 15].

4. **The Holt–Winters method is** universal for the above features, however, a strict determination of seasonality is needed for the data [16]. Perhaps this method would give better results if we split the data quarterly.

The Holt-Winters method can be used:

- in strategic planning: the construction of the main development trend (trend) makes it possible to take into account the upward or downward dynamics of the investigated phenomenon;

- during operational and tactical planning: the revealed seasonal component allows us to note the uneven distribution of volumes over the years in relation to this dynamics.

Exponential smoothing takes into account internal declines and rises in a number of dynamics. It can be used to identify large ups and downs in advance (when applying tactical planning) and be prepared for them. Thus, the method has a fairly large scope. This method is based on the use of a large amount of statistical data, which may not always be relevant. The Holt-Winters method can be used in combined forecasting simultaneously with expert forecasting methods.

5. The **autoregressive model is** similar to the Brown model, a large number of jumps does not allow the model to tune. The use of autoregressive models is based on a preliminary analysis, when it is known that the process under study is largely dependent on its development in previous periods. In some cases, they are used to find a simple transformation leading to a sequence of independent random variables. The scope of the autoregressive model is limited, because in addition to seasonal changes, it does not describe anything. It is rarely used alone. In most cases, a more flexible model is used, including a sliding window [15].

6. **The autoregressive moving average model** may be applicable under the assumption that the time series is stable, that is, its properties do not change over time.

7. **The Box – Jenkins model** can be applied to a large number of data types, but it requires a larger sample (about 40 points for a good forecast) and a thorough study of the behavior of the time series [11]. The disadvantage is that constructing a satisfactory *ARIMA* model is expensive and time consuming.

Until 1982, it was widely believed among forecasters that *ARIMA* models provide the most accurate predictions, since they are more general for a class of other models. However, after conducting the first tests of the forecasting accuracy of various models within the framework of the "*M-Competition"* of the International Institute of Forecasters, during which the *ARIMA* models showed themselves no better than the models of exponential smoothing, this opinion was replaced by a completely logical idea that in each case it is necessary to use own model [16].

FINDINGS

1. When using methods of smoothing by moving average, least squares, Box–Jenkins, as well as Brown models and autocorrelation, the forecast result is affected by the heterogeneity and the presence of intermittent changes in indicators, which lead to a significant decrease in the reliability of forecasting.

2. The application of the Holt-Winters model, which considers the exponential trend (the trend of time series) and additive seasonality (periodic fluctuations observed in the time series), is most suitable for processing statistical data and forecasting for long-term, medium-term and short-term periods taking into account the specifics of a hospital, providing emergency and acute care.

3. The choice of the optimal method for predicting the work of a medical institution, based on identification of the main trends in the time series, taking into account most features when modeling random processes and random events with some random error, allowed us to reduce the relative forecast error.

REFERENCES

1. Karasev NA, Ermolov AS, Turko AP, Kurilin BL, Kislukhina EV. Vliyanie reanimatsionnoy obespechennosti na rezul'taty lecheniya ostroy khirurgicheskoy patologii organov bryushnoy polosti v mnogoprofil'nykh bol'nitsakh g. Moskvy. *Moskovskiy khirurgicheskiy zhurnal*. 2012; (1): 48–54. (in Russ.)
2. Khubutiya MSh, Karasev NA, Kurilin BL, Kislukhina EV, Kiselevskaya-Babinina IV, Molodov VA. Razvitie reanimatsionnogo koechnogo fonda v mnogoprofil'nykh statsionarakh g. Moskvy i ego vliyanie na rezul'taty lechebnoy deyatel'nosti. *Skoraya meditsinskaya pomoshch'*. 2012; 13(3): 45–50. (in Russ.)
3. Yermolov AS, Smirnov SV, Karasev NA, Kurilin BL, Kislukhina EV, Kiselevskaya-Babinina IV, et al. The Analysis of the Main Work Data in the Moscow City Burn Center after Remodeling. *Russian Sklifosovsky Journal "Emergency Medical Care"*. 2016; (1): 60–62. (in Russ.)
4. Khubutiya MSh, Karasev NA, Kislukhina EV, Vasilyev VA, Kurilin BL, Medvedeva AB, et al. Analysis of Clinical and Organizational Activities in the N.V.Sklifosovsky Research Institute for Emergency Medicine in 2005–2015. *Russian Sklifosovsky Journal "Emergency Medical Care"*. 2016; (2): 59–63. (in Russ.)
5. Lukashin YuP. *Adaptivnye metody kratkosrochnogo prognozirovaniya vremennyh ryadov*. Moscow: Finansy i statistika Publ.; 2003. (in Russ.)
6. Svetun'kov SG. *Metody social'no-ehkonomicheskogo prognozirovaniya:* in 2 vol. Saint Peterburg: Izd-vo SpbGUEH Publ.; 2009. (in Russ.)
7. Linnik YuV. *Metod naimen'shikh kvadratov i osnovy matematiko-statisticheskoy teorii obrabotki nablyudeniy*. Moscow: Fizmatgiz Publ.; 1958. (in Russ.)
8. *Pokrovskiy VI, Briko NI (ed.) Obshchaya epidemiologiya s osnovami dokazatel'noy meditsiny. 2-e izd., ispr. i dop. Moskva:* GEOTAR-Media; 2012. 2nd, rev. and ext. Moscow: GEOTAR-Media Publ.; 2012. (in Russ.)
9. Savilov ED, Mamontova LM, Astaf'ev VA, Zhdanova SN. *Primenenie statisticheskih metodov v ehpidemiologicheskom analize*. 2-e izd., dop. i pererab. Moscow: MEDpress-inform; 2004. (in Russ.)
10. Winters PR. Forecasting sales by exponentially weighted moving averages. *Management Science*. 1960; 6(3): 324–342.
11. Orlov AI. *Ekonometrika*. Moscow: Feniks Publ.; 2009. (in Russ.)
12. Pogodin SK. *Metody otsenki portfeley investitsiy, vklyuchayushchikh tsennye bumagi i nedvizhimost'*. Cand. econ. sci. diss. Moscow, 2006. (in Russ.) Available at: https://dlib.rsl.ru/viewer/01003277680#?page=1 [Accessed August 12, 2019].
13. Urbakh VYu. *Matematicheskaya statistika dlya biologov i medikov*. Moscow: Izd-vo Akademii nauk SSSR Publ.; 1963. (in Russ.)
14. Gubinova TV. Primenenie eksponentsial'nogo sglazhivaniya dlya prognozirovaniya vyruchki. *Materialy VII Mezhdunar. stud. nauch. foruma–2015*. Available at: https://scienceforum.ru/2015/article/2015008484 (in Russ.)
15. Osipov LA, Krichevsky AM. Estimation and application of time series models with long memory in economical problems. *Informatsionno-upravliaiushchie sistemy*. 2007; (5): 45–51. (in Russ.)
16. Makridakis S, Andersen A, Carbone R, Fildes R, Hibon M, Lewandowski R, et al. The accuracy of extrapolation (time series) methods: Results of a forecasting competition. *J Forecast*. 1982; 1(2): 111–153.

Received on 19.11.2018

Accepted on 06.03.2019