THE FORESIGHT MODELS IN ANALYZING THE DYNAMICS OF IT SECTOR COMPANIES' DEVELOPMENT

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Information technology (IT) services are an essential component of exports for many countries worldwide, including Ukraine. In 2022, despite a significant economic downturn, the IT sector demonstrated resilience, with computer service exports in certain months reaching up to 48% of total service exports. The growing global demand for computer services creates opportunities to increase foreign currency inflows into Ukraine's state budget. Therefore, analyzing and forecasting IT service exports is crucial for assessing its contribution to the national economy. Since Ukraine's IT sector is predominantly export-oriented, modeling the dynamics of computer service exports allows for insights into the overall state of the industry.

The export of IT services in Ukraine has been analyzed by many scholars. Balashova (2023) identifies directions for developing the export potential of Ukraine's IT industry. Tkachyk et al. (2023) use IT service exports as a key indicator of IT industry development. Their studies primarily focus on theoretical aspects, which do not fully allow for their application in strategic planning. Therefore, mathematical forecasting of computer services export volumes is an important task for assessing potential and effectively planning the activities of Ukraine's IT sector and the national economy.

One of the most common tools for time series forecasting is the Autoregressive Moving Average (ARMA) models, which allow for high accuracy in predicting future values based on past data. Therefore, the aim of this study is to apply the ARMA models (ARIMA, SARIMA) to forecast the export volumes of computer services, which will help identify key trends and potential seasonal fluctuations in this field. The research can provide insights into the potential future growth of the country's IT sector and create development scenarios under different market conditions.

The general algorithm for building an ARIMA model includes the following steps: checking the time series for stationarity, transforming the time series into a stationary form through discrete differentiation, calculating the autocorrelation and partial autocorrelation coefficients, estimating model parameters, and checking the model for adequacy. Thus, building an ARIMA model for a specific time series involves selecting the optimal values for parameters p, d, and q, where p is the order of autoregression (AR) indicating the number of previous values used for forecasting, d is the differencing order indicating how many times the series has been differenced to achieve stationarity, and q is the order of the moving average (MA) component, specifying the number of prior error terms included in the model. In cases where seasonality is present in the time series, additional parameters P, D, Q, and s should be considered, where P, D, and Q represent the order of autoregression, differencing, and moving average components for the seasonal component, considering the seasonal period s. This model is known as SARIMA, and its parameters can be denoted as SARIMA(p, d, q) × (P, D, Q, s).

The input data for this study comprises foreign trade statistics from the National Bank of Ukraine (NBU), specifically the monthly dynamics of computer service exports from the beginning of 2015 to September 2024 (*External Sector Statistics. External trade*, 2024). The Python programming library statsmodels was chosen as the tool for analysis and modeling.

A preliminary visual analysis of the data (Fig. 1) shows a clear upward trend in computer service exports up until 2022, after which there was a sharp decline, followed by a moderate downward trend.

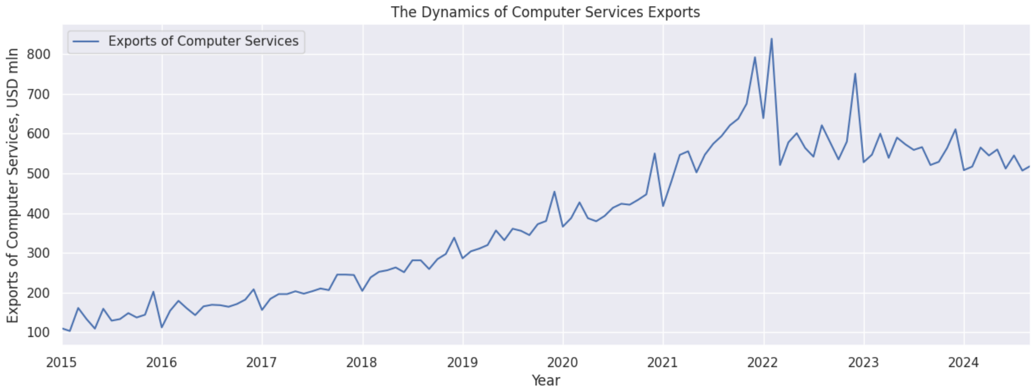

Figure 1 – The Dynamics of Computer Services Exports. Source: National Bank of Ukraine
Source: National Bank of Ukraine

Seasonality can also be observed in the data on the graph. Specifically, the export values in the last month of the year are always significantly higher than in preceding periods. This seasonal factor becomes more evident after decomposing the time series into its trend, seasonal, and residual components. The plots of these components are shown in Figure 2.

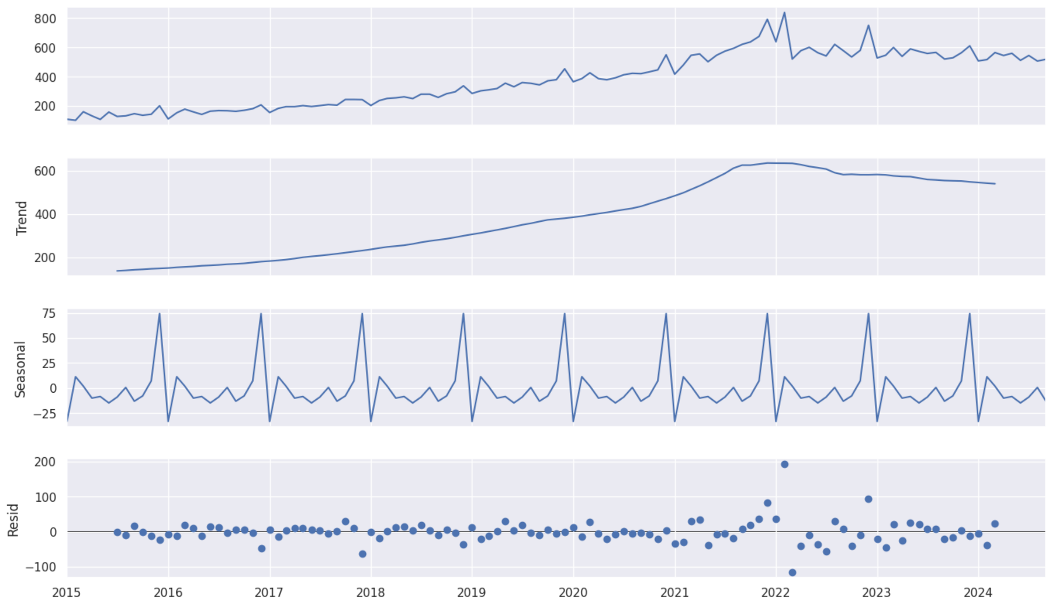

Figure 2 – Trend- Seasonal Decomposition of Time Series

The presence of trend and seasonality in the data indicates the non-stationarity of the time series and the need to transform it into a stationary form. To more accurately test for stationarity, the Dickey-Fuller test was applied. The calculated test statistic is 1.18, which is higher than the critical value of 2.89 at the 95% significance level, with a p-value of 0.68. This confirms that the time series is non-stationary. To achieve stationarity, the time series required differencing twice. After this transformation, the recalculated Dickey-Fuller test statistic is 10.99, which is significantly lower than the critical value, with a p-value close to zero. Therefore, the parameter d for the SARIMA model should be set to 2.

The remaining model parameters were selected through a grid search, identifying the optimal parameter set by maximizing the Log Likelihood function and minimizing the Akaike Information Criterion (AIC) among the constructed models. As a result of building models with various parameters, the optimal model was determined to be SARIMA(3, 2, [0,1])x(1,0,1,12). This model has a Log Likelihood value of -600.313 and an AIC of 1214.626. The parameter estimates for the model are shown in Figure 3.

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-1.6611	0.127	-13.037	0.000	-1.911	-1.411
ar.L2	-0.9818	0.193	-5.092	0.000	-1.360	-0.604
ar.L3	-0.3174	0.118	-2.700	0.007	-0.548	-0.087
ma.L2	-0.9864	0.203	-4.856	0.000	-1.385	-0.588
ar.S.L12	0.9968	0.058	17.262	0.000	0.884	1.110
ma.S.L12	-0.9496	0.454	-2.091	0.037	-1.839	-0.060

Figure 3 – The Estimated Coefficients for the Parameters of the Model

To assess the predictive accuracy of the model, we calculated model values and compared them with actual values using the Mean Absolute Percentage Error (MAPE). The MAPE is 7.93%, which is a low value, indicating a high predictive power of the model. Additionally, a residual analysis was conducted to evaluate model adequacy. The residuals are normally distributed, show no autocorrelation, and have a constant variance, except for shock variables in the data due to the onset of full-scale war. Therefore, this model is suitable for forecasting.

A chart of forecasted values for the next six months, with a 95% confidence level, is presented in Figure 4.

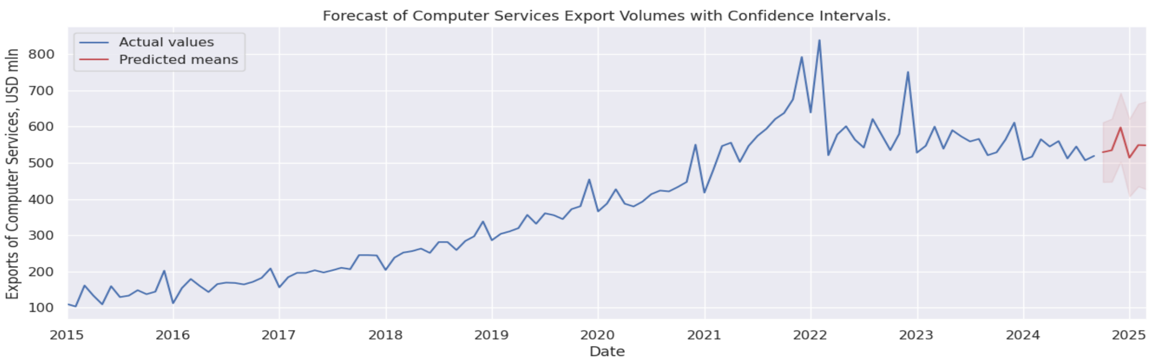

Figure 4 – Forecast of Computer Services Export Volumes with Confidence Intervals

The forecasting results indicate that the dynamics of computer services exports will remain stable over the next six months. By December 2024, computer services exports are projected to reach approximately $600 million, a figure close to last year's level. This forecast confirms that the IT sector remains resilient to wartime shocks and is capable of providing a steady inflow of foreign currency into the national budget, consistent with the levels of the past two years.

References:

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