Prediction of the Consumer Price Index of Norway

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***Abstract*—This paper explores the Norwegian Consumer Price Index (CPI) from 1990 until 2022. The data was divided into train and testing, using the 80-20 rule. First, it was carried out a global analysis of the time series (TS) finding that the original TS wasn't stationary, and, based on that, an additive model was chosen to separate the TS into trend, seasonality, and erratic components. The stationarity of the erratic component was also checked with the Dickey-Fuller (DF) test, confirming its stationarity at a significance level of 95%.**

***Index Terms*—CPI, Time Series, Forecasting**

I. Introduction

The Consumer Price Index (CPI) is one of the most important macroeconomic indicators of a country. The CPI is an indicator used to calculate a nation's inflation rate, since it monitors monthly fluctuations in the value of a nation's currency as well as the cost of a variety of goods and services, hence the great importance of CPI forecasting [1]. This paper explores the Norwegian CPI index, first by analysing its past values, then it tries to forecast its future values.

The data contains the monthly CPI from 1950, but for the purpose of this work, the project focuses on the data from 1990 until August 2022. Later in this project, CPI values from other countries will be used to predict the Norwegian CPI. In total, it were used 329 samples, 313 for training the predictive models and for the exploration and 79 for assessing the models' performance, equivalent to an 80-20 split of the data.

Forecasting CPI has a great importance for a country. Álvarez-Díaz et Al. studied the influence of non-linear, Neural Networks and Genetic Programming, models against linear ones, Autoregressive (AR) and SARIMA, in forecasting the US CPI Indicator [5]. Their work concluded that use of non-linear models doesn't lead to better results, especially since the best model they obtained was SARIMA, although it did not achieve significantly better results.

In 2020, Riofrío et Al. carried out a comparative study of different predictive models to forecasting Ecuador's CPI from January 2005 to June 2019 [3]. Some models tested were Support Vector Regression (SVR), Neural Networks with Long Short-Term Memory layers, Seasonal Autoregressive Integrated Moving Average (SARIMA), Exponential Smoothing and Facebook's Prophet. The models were also optimized using grid-search to find the best hyperparameters. Using the last 12 months to evaluate the models, their study concluded that the model with the lowest Mean Absolute Percentage Error (MAPE) was the SVR, followed by the LSTM and SARIMA.

A similar approach was followed by Shinkarenko et Al. [4], when they predicted Ukraine's CPI from 2010 until 2020. In their work, they first analysed the data, based on trend, seasonality and them used the Box-Jenkins (ARIMA) and Exponential Smoothing models to predict the CPI of October and November 2020.

Nguyen et Al. [2] used more modern approaches to predict the monthly CPI index from the United States from 2017 until 2022. First, they divided into 80-20 for training and testing, then they tested several models, including multivariate ones, such as Multivariate Linear Regression (MLR), SVR, Autoregressive Distributed Lad (ARDL), and Multivariate Adaptive Regression splines (MARS) for forecasting. The CPI variable also relied on additional independent variables, such as the crude oil price, the global gold price, and the federal fund effective rate. In their experiments, they concluded that the SRV model achieved better results on the train data, but the MARS model was the winner on the test data.

In short, different approaches have been tested by many authors to predict a country's CPI. The most suitable technique seems to differ from dataset to dataset, and there is no general technique that always produces good results. It should also be noted that multivariate techniques seem to provide good results for predicting a dependent variable, but they require more data, which is not always possible.

The remainder of the paper is organized as follows. Section II presents a description of the methods developed throughout the project. In Section III, the results obtained by the different techniques tested are detailed. Section **??** summarizes the main findings of this paper. Finally, Section **??** presents the conclusions of these papers and the future work that needs to be done.

II. Methods

The initial dataset had a lot of data that wasn't relevant to the problem. As a result, it needed to be decluttered. Additionally, the date and time information wasn't in the proper format to be used. As a result, after the dataset had been tidied up, it only had a first column for the date and time, then a column for the CPI index of each country.

The data was then divided into training a testing data, using the rule of 80% for training and 20% for test. With the data divided, the training part was used for characterization of the

TS, modelling and training. The test data was saved for later evaluation of the forecast models' performance.

With the selected TS, the first task was to do a brief analysis of it. It was checked if it had missing values, confirming that it had not. Following that, the stationarity of the TS was examined. First, it was analysed through the visualization of the time series (TS), and it was observed that the TS had a clearly increasing trend and some seasonality (see Figure 1). This concluded that the TS isn't stationary. In addition to the visual analysis of the stationarity, the Dickey-Fuller (DF) test was applied to confirm the results through **empirical observation**. Using a significance level of 95%, the DF statistical test assumed the hypothesis:

- H0: The TS is non-stationary;
- H1: The TS is stationary;

The test (see Table I) verified that the TS is non-stationary. This same statistical test was used throughout the project to determine whether the TS was stationary, always using the same hypothesis and significance level As the original TS is non-stationary, it needs to be transformed in order to become it. To achieve this, it was employed a decomposition model. These models are based on the idea that the TS have trend and cyclic parts, and they divide the TS in its trend, seasonal and erroneous (residuals) components.

To determine the appropriate decomposing model for the problem ahead, it was analysed the magnitude of the values. The two main choices, as the values are distant from zero, are the additive or the multiplicative model. When the order of magnitude of values does not change throughout time, it's used an additive model, otherwise a multiplicative model should be applied. As it can be observed by the Figure 1, the order of magnitude doesn't change over time, so it was applied an additive model.

In the additive model, the TS trend is represented by $x(n) = tr(n) + sn(n) + e(n)$, where $x(n)$ is the time series, $tr(n)$ the trend component, $sn(n)$ the seasonal component, and $e(n)$ the erratic component.

First, The trend was removed by fitting a model for the 1^{st}, 2^{nd} and 3^{rd} order trends. After select the most appropriate, the trend adjusted TS was calculated by subtracting the trend to the original TS. The trend adjusted TS was initially subjected to a frequency analysis. With this information, a low-pass filter was applied to the TS while taking the most crucial frequencies into consideration to calculate the seasonality using a Butterworth low-pass filter. Once the seasonal component had been identified, the erratic component was determined by removing the seasonality from the trend adjusted TS. The order of the fitting model and filter was adjusted according to results achieved by the Dickey-Fuller test.

Another approach to reach a stationarity is by differencing. Initially, the trend is removed by the 1^{st} order differentiation. After that, the seasonality differencing is applied with a period of 12, equal to the number of samples per year.

These two approaches were evaluated and the one that achieved better results in the DF test, was used in the next steps of the process. The Autocorrelation Sequence (ACS) of the two approaches was also tested. However, it was not applied merely to visually observe how the time series behaved. In the next stage of the project, this will be important in choosing the type of linear model that represents the stationary TS.

III. RESULTS

The Section present the main results found in this work. First, it presents an overall analysis of the Norwegian CPI value. After that, it presents the work made to convert the time series into stationary.

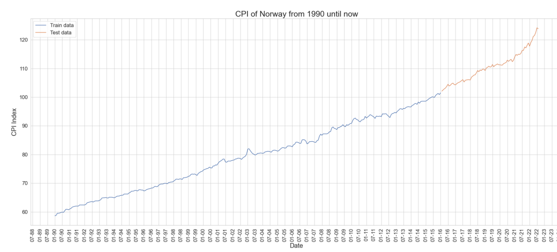

Fig. 1: CPI Index of the Norway from 1990 until 2022

In a first analysis of the TS (see Figure 1), it can be observed an increasing trend and patterns repeated every 6 months, and every year. In addition, it can be seen that the order of magnitude of the values does not seem to vary over time, so an additive decomposition model was used. After careful examination of the Time Series, it seems that the trend shifts from a linear trend to a larger order trend after 2020. This shift can be explained by the COVID-19 era, which altered the world and caused huge economic changes. Since this shift appears only on the test data, in the future, the models could have difficulties in correctly forecast the test data.

A. Basic Transformations on the TS

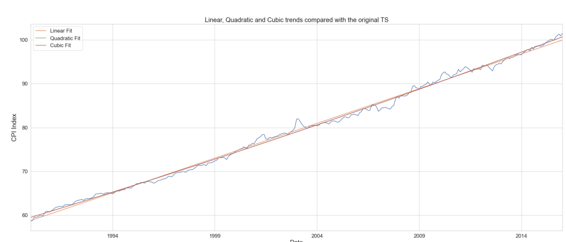

Fig. 2: 1^{st}, 2^{nd} and 3^{rd} order trends compared with the original TS

In Section II it was concluded that one possible approach to transform the series into stationary was using an additive model to decompose it. Therefore, to transform the TS in stationary, the first step was to remove the trend. This was achieved using model-fitting, where the 1st, 2nd and 3rd order trends were tested. According to the results (see Figure **??**), the 1st order trend was adequate for the problem, since it is a simpler model and the differences to the other orders are insignificant.

After removing the trend by subtraction from the original series, it can be seen more clearly the seasonal patterns of the TS (see Figure 4). The patterns seem to repeat every six months, every year, and approximately every five years. The results were further strengthened by the Discrete Fourier Transform (DFT) (see Figure 3), where it can see the peaks at T=0.5 (6 months), at T=1 (every year) and at T=5 (every 5 years). It was also found that the most important seasonal component is 2/3 months. After testing several cut-off points for the Butterworth filter, it was decided to use a cut-off point of 2.2, to pick only the most important frequencies and with an N=5.

With the trend adjusted series and the seasonal component, it was calculated the erratic component was calculated by once again subtracting the seasonal component to the trend adjusted series. Figure 5 shows these components isolated from one another, as well as the effect of each on the TS.

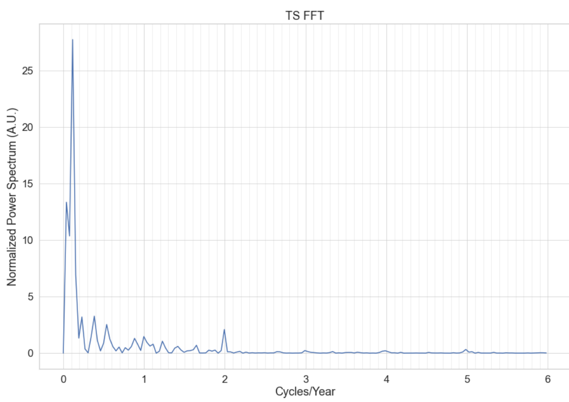

Fig. 3: Frequency analysis of the trend adjusted TS

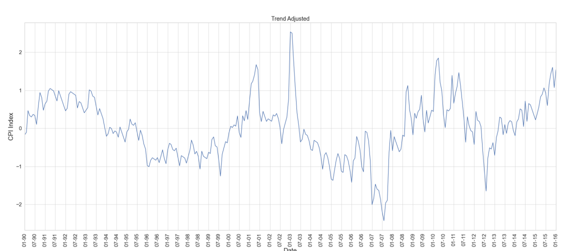

Fig. 4: Original TS compared with the trend adjusted version by model-fitting

The second approach to transform the TS in stationary was using differencing. The results in Figure 6 show that there still seems to be some seasonality. In order to confirm the results of the two approaches empirically, the DF test was applied.

Table I presents the p-values obtained by the approaches. Although both obtain a p-value of 0.0, meaning that the final

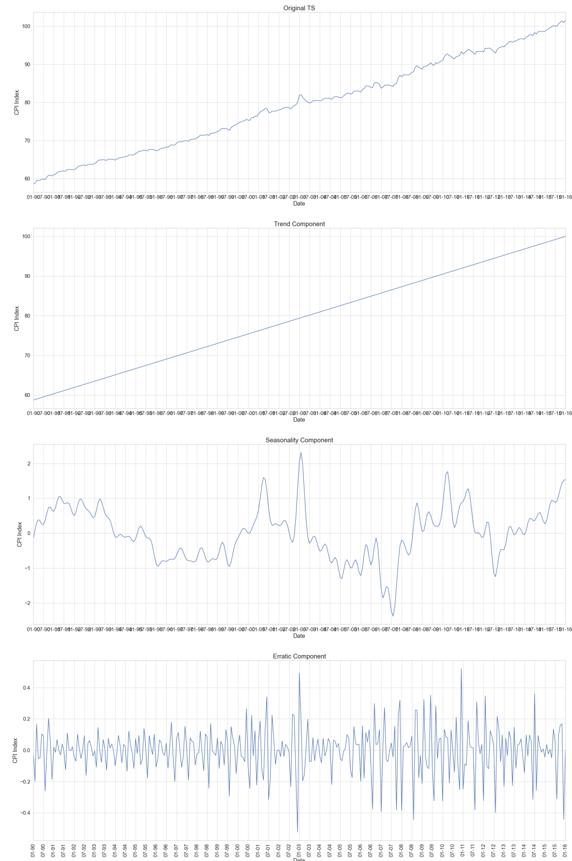

Fig. 5: Additive model components compared with the original TS

	Original TS	1st Approach	2nd Approach
ADF Statistic	1.00	-17.22	-7.24
p-value	0.99	0.0	0.0
Critical Value 1%	-3.45	-3.45	-3.45
Critical Value 5%	-2.87	-2.87	-2.87
Critical Value 10%	-2.57	-2.57	-2.57

TABLE I: DF Statistical Test. 1st approach: Trend as seasonal adjusted by model-fitting and filtering; 2nd approach: Trend and seasonal adjusted by differencing

TS is stationary, the 1st approach shows an ADF statistic that is furthest from the critical points, and this was chosen to proceed to the next stages of the project.

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A further analysis of the stationary TS was carried out. Figure 7 presents the ACS values of the stationary TS using a significance level of 95%. The ACS shows a rapid decrease, reaching a value close to zero, which indicates that the series is stationary.

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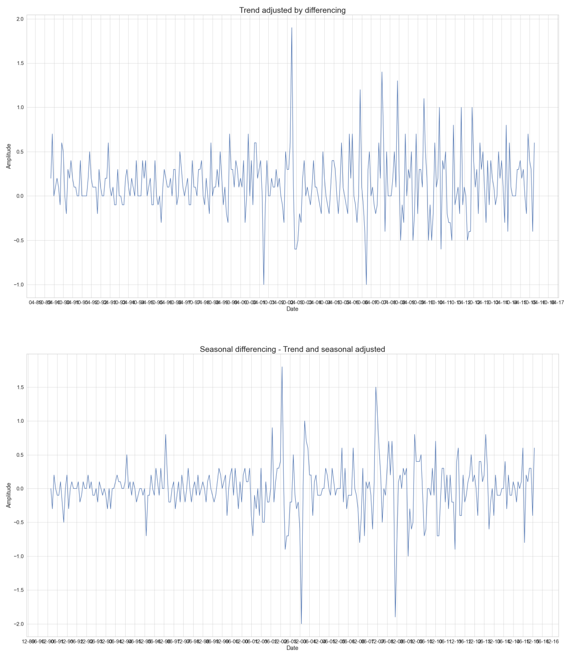

Fig. 6: Trend and seasonal TS adjusted by differencing

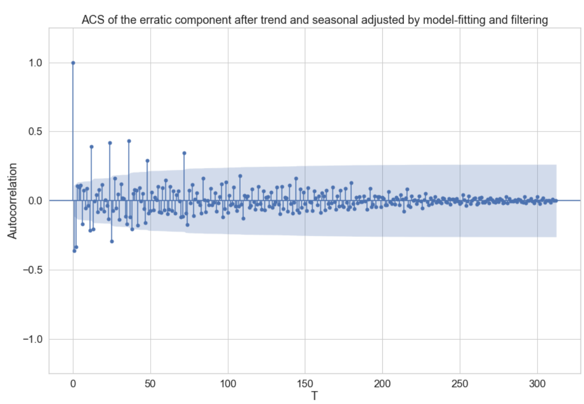

Fig. 7: Autocorrelation Sequence of the stationary Time series

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