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COMPARISON OF UNIVARIATE AND HEURISTIC FORECASTING MODELS IN THE EMPLOYMENT/UNEMPLOYMENT SECTOR IN MALI

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ABSTRACT

Unemployment has always been a problem in Mali, as it is today. Using the actual data from the "World Data Atlas" data source, this study aims to perform a series of forecasting operations using some of the accepted univariate forecasting models in literature and a set of heuristic ones, so as to see which one will hold less error percentage, and thus give the best estimate on how the future numbers might look like. The results enable a comparison of univariate and heuristic techniques.

Keywords: Univariate Forecasting, Heuristic Forecasting, Bootstrapping, Parsimony, Mali, Unemployment

JEL Classification: C02, C53,C60

MALİ'DEKİ İŞSİZLİK ORANLARI İÇİN TEK DEĞİŞKENLİ VE SEZGİSEL TAHMİN MODELLERİNİN KARŞILAŞTIRILMASI

Mali'de işsizlik, her dönemde olduğu gibi bugün de önemli bir sorundur. "Dünya Veri Atlası"ndan elde edilen verilerin kullanıldığı bu çalışmada, tek değişkenli tahmin modelleri ile sezgisel tahmin modelleri kullanılarak, en düşük hata oranını veren ve dolayısıyla gelecekteki işsizlik rakamlarını olabildiğince gerçeğe yakın tahmin eden tahmin modeli elde edilmeye çalışılmıştır. Sonuçlar, tek değişkenli tahmin teknikleri ile sezgisel tahmin teknikleri arasında bir karşılaştırma yapmaya olanak sağlamaktadır.

Anahtar Kelimeler*:* Tek Değişkenli Tahmin, Sezgisel Tahmin, Bootstrapping, Basitlik, Mali, İşsizlik

JEL Sınıflandırması: C02, C53,C60

1. INTRODUCTION

Forecasting is an activity or process through which someone predicts or attempts to predict the future, based on previous events or on some information he/she has now. In short it is a guess, but logical and rational, about what is going to happen in the future. It's about capturing the regularities in a data and using them to make predictions. It is used in various fields such as economy, weather, supply chain, planning, manufacturing, quality management,

demand, scheduling, etc. Forecasting isn't something which has been created, but rather it has always existed.
Quantitative Forecasting: based on historical/past data or information. The data is a numerical measurement expressed in terms of numbers. That data is analysed in order to discern some trends or patterns which repeat more than once and use those to make some predictions. The data is usually spread over a long period of time and is usually continuous, thus it is referred to as "Time Series". There are many available techniques for forecasting. Most of them are case specific, that is one algorithm may not perform well in every situation. There are a number of accepted algorithms/techniques in the literature. In this study, several univariate techniques are utilized. However, because of the nature of forecasting itself, that is there will never be a perfect method for every situation, many heuristic techniques have been developed, too. Several of these heuristic techniques will be utilized in this study. These techniques deal with data samples which have a small size (usually less than 40). The reason behind choosing these specifically is that the data which will be used in this study has a size of 27.

There are techniques that are mostly case oriented, often the result of different combination of methods; these methods are referred to as 'hybrid models' (Fajardo-Toro, Mula, Poler, 2018). ARIMA+ANN, kNN+SVM, Grey+Evolutionary algorithms are a few examples of such methods.

2. MATERIALS

The data which is used in this study (Niangadou, 2018) is from World Data Atlas (WDA) (Knoema, 2017) which is under "Knoema". Knoema is a free resource for statistical data. It offers a wide range of data and information about all the countries in the world, collected from highly reliable sources such as the World Health Organisation and United Nations (UN). The data taken from WDA consists of the unemployment rates of Mali arranged in order from 1990 to 2016, on a yearly basis, that is 27 entries in total as can be seen in Table 1. The values/rates give the number of unemployed persons as a percentage of the total labour force. It's very hard to find any information about the employment situation prior to the early 90s.

Table 1: Yearly Unemployment rates of Mali from 1990-2016

Year	Unemployment (%)	Year	Unemployment (%)
1990	7.0	2004	8.8
1991	7.2	2005	9.6
1992	7.1	2006	10.4
1993	12.2	2007	11.7
1994	11.9	2008	10.6
1995	7.4	2009	9.4
1996	8.0	2010	7.3
1997	3.3	2011	6.9
1998	7.4	2012	6.9
1999	9.3	2013	7.3
2000	7.9	2014	8.2
2001	7.6	2015	8.1

2002	7.3	2016	8.1
2003	4.5		

In order to overcome the problem of working with a small dataset, a popular technique which helps increase sample sizes will be introduced. The technique is called "Bootstrapping" (Efron and Tibshirani, 1993). It's a powerful statistical technique, accepted in literature, which involves resampling. It generates new data from an initial data sample, which usually has a sample size of less than 40. It was first mentioned in 1979 by Bradley Efron (1979) and since then different procedures have been developed (Singh, 1981; Efron, 1987; DiCiccio and Efron, 1992).

The method is sometimes referred to as "Sampling with replacement". This basically means that when a value is drawn from a pool/set, instead of putting that value aside, it is possible to draw it a second time, or even more than twice, and because some observations may be resampled more than one time, others might not be sampled at all. A first bootstrap sample is generated by drawing random observations from the initial data set, and the average of that sample is calculated. This process is performed n times so as to have at the end a "bootstrap sample of the means".

For this study, since there are 27 original values in the data, a new data with a sample size of 27x4, which is 108, will be generated. Since only one dataset will be used in this study, it is therefore logical to use scale-dependent measurement techniques to assess the forecast accuracy. Some popular models are the Mean squared error (MSE), Mean absolute error (MAE) and Root mean squared error (RMSE). The lower the values of these are, the more satisfactory the forecasts will be (DeLurgio, 1998).

3. APPLICATION OF THE METHODS

Several of the previously mentioned methods are applied on the data, univariate and heuristic techniques. In Section 3.1, the methods are applied on the unemployment rates of Mali between 1990 and 2016, which is referred to as the initial dataset; and Section 3.2 shows the application of those methods on the data obtained after bootstrapping the initial dataset, which is referred to as 'Sample 10'.

3.1. Forecasting with the initial dataset

Here, for every algorithm, the first 22 entries of the data will be used to set up the models, and the last 5 entries to test the model. The time series plot of the data is shown in Figure 1. Looking at the graph, it can be seen that the data shows no trend or seasonal patterns. Related tests also show that the series is white noise. Therefore, it can be concluded that simple moving averages and single exponential smoothing methods are suitable for this case. And an ARIMA model is not applicable.

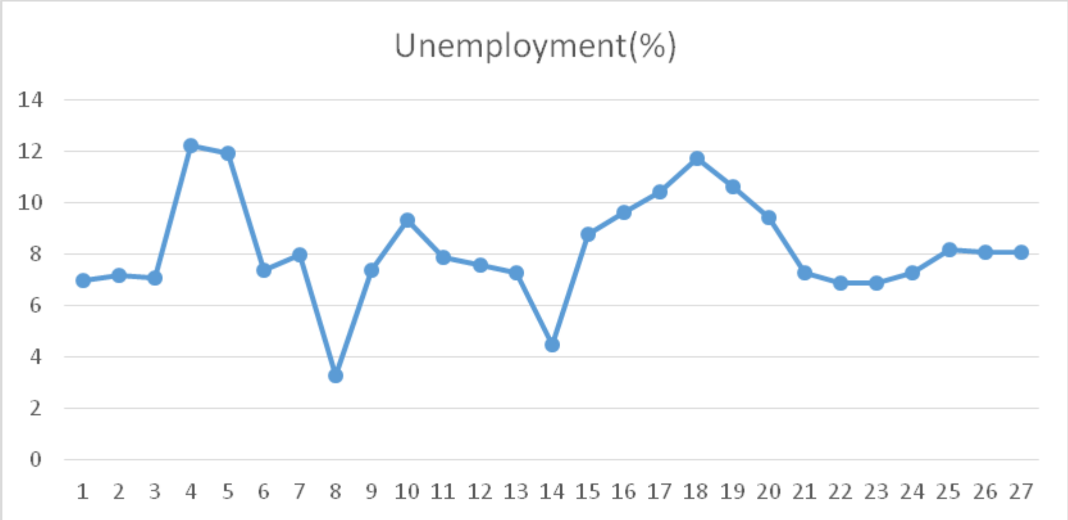

Figure 1: Unemployment Rates of Mali from World Data Atlas

3.1.1. Simple moving averages

In this univariate technique, the more periods used in a moving average, the worse the forecasts will be. Therefore, it is convenient to use a 3-period simple moving average here, that is, 3 observations will be included in each average. The following is the equation for that:

$T_t = (Y_{t-1} + Y_t + Y_{t+1})$, where $t = 1, 2, 3, 4, ..., n-1$ and

where Y is the observed value at time t.

This operation is repeated over and over until the end of the data. Comparing those results with the observed ones, the errors are computed and the MAE, the MSE and the RMSE are found to be 0.8611, 1.4619 and 1.2, respectively.

3.1.2. Single exponential smoothing

The general equation for single exponential smoothing, which is a univariate forecasting technique, is as follows:

$$F_{t+1} = F_t + \alpha*(Y_t - F_t)$$

where Y_t is the observed value at time t and F_t the predicted value. It is commonly assumed that the initial value F_0 is the first observed value (first entry in the table). For this case, the values 0.2, 0.5, 0.7 and 0.9 have been used for the parameter α.

The error for each case is as follows:

For α = 0.2, the MAE = 1.203 and MSE = 2.935

For α = 0.5, the MAE = 0.784 and MSE = 1.152

For α = 0.7, the MAE = 0.464 and MSE = 0.410

For α = 0.9, the MAE = 0.146 and MSE = 0.046

The value of α = 0.9 yields the minimum MAE and MSE, therefore that value of α is the most appropriate for this case. Its RMSE value is 0.214.

3.1.3. Original grey model - GM(1,1)

There are several steps for building a grey differential equation or model, which is a heuristic technique (Chen and Chang, 1998). The first 22 entries of the data set will be used to set up the model.

First of all, the initial series $X^{(0)}$ is equal to the first 22 entries, that is $X^{(0)}(k)$ = {7, 7.2 , 7.1 , 12.2 , ..., 9.4 , 7.3, 6.9}.

After this, the new series $X^{(1)}$ is generated using $X^{(0)}$. $X^{(1)}(k)$ = {7, 14.2 , 21.3 , 33.5 , 45.4 , 52.8 , 60.8 , 64.1 , 71.5 , 80.8 , 88.7 , 96.3 , 103.6 , 108.1 , 116.9 , 126.5 , 136.9 , 148.6 , 159.2, 168.6 , 175.9, 182.8}

Using these values, parameters of *a* and *b* are estimated. The estimate values of *a* and *b* are -0.00386 and 8.009 respectively. Finally, the values of *a* and *b* are put into the Grey model and the following equation is obtained

$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) – (b/a)]*(1 - e^{a})*e^{-a(k-1)} = [x^{(0)}(1) + (8.009/0.00386)]*(1 – e^{-0.00386})*e^{0.00386(k-1)}$

with the initial value of $x^{(0)}(1) = 7$.

The values for the next 5 years can now be predicted.

for k = 23, $\hat{x}_0^{(0)}(23) = [7 + 2074.87]*(1 – e^{-0.00386})*e^{0.00386(23-1)} = 8.72$

for k = 24, $\hat{x}_0^{(0)}(24) = [7 + 2074.87]*(1 – e^{-0.00386})*e^{0.00386(24-1)} = 8.75$

for k = 25, $\hat{x}_0^{(0)}(25) = [7 + 2074.87]*(1 – e^{-0.00386})*e^{0.00386(25-1)} = 8.79$

for k = 26, $\hat{x}_0^{(0)}(26) = [7 + 2074.87]*(1 – e^{-0.00386})*e^{0.00386(26-1)} = 8.82$

for k = 27, $\hat{x}_0^{(0)}(27) = [7 + 2074.87]*(1 – e^{-0.00386})*e^{0.00386(27-1)} = 8.86$

The MAE, MSE and RMSE are calculated and their values are 1.068, 1.3718 and 1.17 respectively.

3.1.4. Grey prediction with rolling mechanism

Another heuristic technique is grey prediction with rolling mechanism. Since predictions for five periods need to be made, five different GM(1,1) models will be needed (Akay and Atak, 2007). For simplicity, only the results will be shown here, that is the final equations and the predicted values. The first step of the method is the combination of all the steps/work in a basic GM(1,1). Therefore, the final equation obtained in the previous section (Section 3.1.3) will be used in the first step.

Step 1: the first model is as follows:

$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) + (8.009/0.00386)]*(1 – e^{-0.00386})*e^{0.00386(k-1)}$

with $x^{(0)}(1) = 7$.

For k = 23, the predicted value is $\hat{x}_0^{(0)}(23) = 8.72$.

The first data $x^{(0)}(1) = 7$ is removed and 8.72 is the new entry added to the data.

Step 2: the new value of $x^{(0)}(1)$ is the second element of the initial series $X^{(0)}$, that is

$$x^{(0)}(1)_{new} = x^{(0)}(2) = 7.2.$$

Also as mentioned before, 8.72 is added to the end of the data. The new model is generated using the new data.

Step 3: the new model is

$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) + (8.21/0.00237)]*(1 - e^{-0.00237})*e^{0.00237(k-1)}$ with $x^{(0)}(1) = 7.2$.

For k = 24, the following value is obtained: $x^{(0)}(24) = 8.67$.

This new value is added to the series/data and $x^{(0)}(1) = 7.2$ is removed. Now

$x^{(0)}(1)_{new} = x^{(0)}(3) = 7.1$

of the initial data series used in step 1. Another model is generated again.

Step 4: the new model is as follows

$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) + (8.47/0.00057)]*(1 - e^{-0.00057})*e^{0.00057(k-1)}$ with $x^{(0)}(1) = 7.1$

For k = 25, the following is obtained: $x^{(0)}(25) = 8.59$.

Again this value is added, $x^{(0)}(1) = 7.1$ is removed from the data and

$x^{(0)}(1)_{new} = x^{(0)}(4) = 12.2$

from the original data and another model is generated.

Step 5: the new model is as follows

$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) + (7.68/0.0068)]*(1 - e^{-0.068})*e^{0.068(k-1)}$ with $x^{(0)}(1) = 12.2$

For k = 26, the predicted value is: $x^{(0)}(26) = 9.17$.

Now, the last model is generated with $x^{(0)}(1)_{new} = x^{(0)}(5) = 11.9$.

Step 6: the last model is as follows

$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) + (6.63/0.0186)]*(1 - e^{-0.0186})*e^{0.0186(k-1)}$ and $x^{(0)}(1) = 11.9$

For k = 27, the prediction for the last period is: $x^{(0)}(27) = 11.01$

In summary, the forecast values for period 23 to 27 are:

k = 23, $\hat{x}_0^{(0)}(23) = 8.72$
k = 24, $\hat{x}_0^{(0)}(24) = 8.67$
k = 25, $\hat{x}_0^{(0)}(25) = 8.59$
k = 26, $\hat{x}_0^{(0)}(26) = 9.17$
k = 27, $\hat{x}_0^{(0)}(27) = 11.01$

The errors for the last five periods are 1.512, 2.99 and 1.729 for the MAE, the MSE and the RMSE respectively.

3.1.5. Grey model with Optimization of Background Value

In this heuristic technique, the first thing to do is to estimate the value of parameter *a* using the following equation.

$a(k) = \ln x^{(0)}(k) - \ln x^{(0)}(k-1)$

For every value of k = 2,3,...,22 a new value of a is obtained and at the end, those values are averaged to obtain the final value of

$a = \Sigma a(k)/21 = -0{,}0003$.

Next, the background value needs to be estimated for every value of k between [2, 22] using the following equation.

$$z^{(1)}(k) = \frac{x(0)(k)}{\ln x^{(0)}(k) - \ln x^{(0)}(k-1)} + \frac{[x^{(0)}(k-1)]^{k}}{[x^{(0)}(k)]^{k-2} * [x^{(0)}(k-1) - x^{(0)}(k)]}$$

After that, the parameter *b* needs to be estimated in its turn, for every single value of $z^{(1)}(k)$, using the following equation.

$$b(k) = x^{(0)}(k) + a * z^{(1)}(k) \qquad \text{for } a = -0{,}0003$$

which is the value calculated above and k = 2,3,...,22. The final estimate of *b* is the average of all the *b(k)* which is found to be

$b = \Sigma b(k)/21 = 8{,}1489$.

Finally, using the the values of *a* and *b,* the following Grey prediction model is obtained:

$$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) - (b/a)]*(1 - e^{a})*e^{-a(k-1)} = [7 + (8.1489/0.0003)]*(1 - e^{-0,0003})*e^{0,0003(k-1)}$$

Now, the values of year 2012 to 2016 can be predicted through k values of 23, 24, 25, 26 and 27 respectively. They are:

Year 2012: k = 23 → $\hat{x}^{(0)}(23) = 8{,}203$
Year 2013: k = 24 → $\hat{x}^{(0)}(24) = 8{,}206$
Year 2014: k = 25 → $\hat{x}^{(0)}(25) = 8{,}208$
Year 2015: k = 26 → $\hat{x}^{(0)}(26) = 8{,}211$
Year 2016: k = 27 → $\hat{x}^{(0)}(27) = 8{,}213$

Finally, the MAE, the MSE and the RMSE are computed and their values are 0.4882, 0.5087 and 0.71, respectively.

3.2. Forecasting with the bootstrap dataset

As explained before, a set with the sample size of 108 was generated from the initial data set. Minitab is used for this purpose. In order to find a bootstrap data set which most resembles the initial data set, 10 bootstrap data sets (Sample 1 through 10) were created and the one with the closest mean and standard deviation to the original/initial data set's was chosen. The chosen set, "Sample 10" was used for forecasting.

Figure 2 shows the time series plot of the data from time t = 1, which represents the first quartile of year 1990, to time t = 108, which is quartile 4 of year 2016. For every algorithm used next, the first 88 entries of ‘Sample 10’ were used to set up each model, and the remaining 20 entries were used to test each one of them and estimate the errors. To compare the results with the one obtained from the initial data set (of 27 entries), it is therefore logical to predict for 5 periods with the next algorithms as well. The last 20 entries, therefore, represent the quartile values of the years 2012, 2013, 2014, 2015 and 2016, respectively.
Relevant tests show that this series, as expected, is also white noise. Thus, an ARIMA model is not applicable.

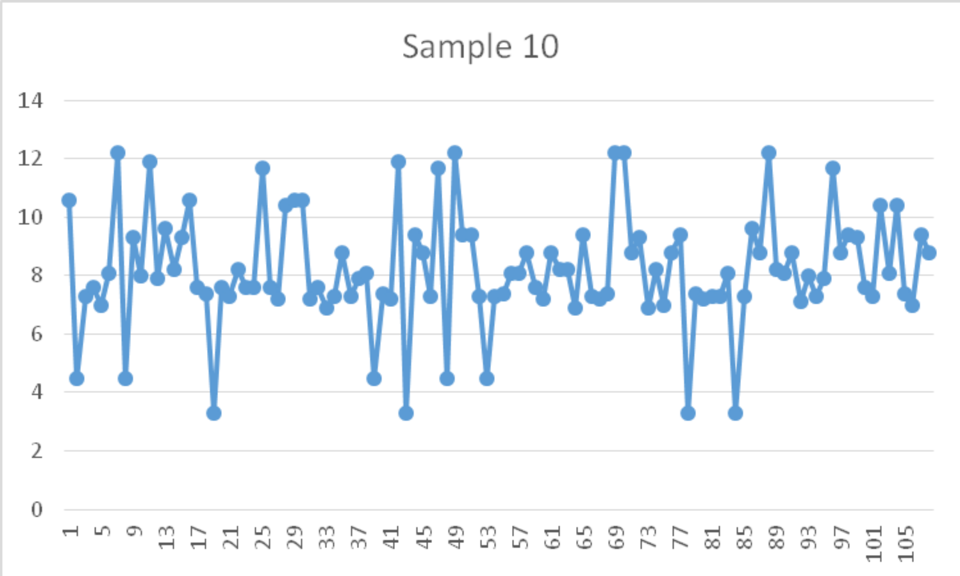

Figure 2: Time series plot of ‘Sample 10’

3.2.1. Simple moving averages

It is convenient to use a 3-period simple moving average here as well, utilising the following equation:

$$T_t = (Y_{t-1} + Y_t + Y_{t+1}) , \qquad \text{where } t = 1, 2, 3, 4, ..., n-1$$

where Y is the observed value at time t and n = 108.

The whole data set is used here, that is, all 108 entries will be needed.
The results obtained are compared with the observed values, the errors are computed and the MAE, the MSE and RMSE are found to be equal to 1.29, 2.83 and 1.68, respectively.

3.2.2. Single exponential smoothing

Since the series is white noise, a single exponential smoothing model is suitable for this data.
The values 0.2, 0.5, 0.7 and 0.9 have been used again for the parameter α. The error for each value of α is as follows:
For α = 0.2, the MAE = 1.195 and MSE = 2.839
For α = 0.5, the MAE = 0.831 and MSE = 1.296
For α = 0.7, the MAE = 0.539 and MSE = 0.540
For α = 0.9, the MAE = 0.194 and MSE = 0.072

The value of α = 0.9 yields the minimum MAE and MSE, therefore that value of α is the most appropriate for this case. The resulting RMSE is equal to 0.268

3.2.3. Original Grey Model GM(1,1)

The process here will be the same as in the example in Section 3.1.3, but with the data of 'Sample 10'. The first 88 entries of the data set will be used to set up the model.

The initial series $X^{(0)}$ is equal to the first 88 entries, that is $x^{(0)}(k) = \{10.6 , 4.5 , 7.3 , 7.6 , ... , 8.8 , 12.2\}$.

The new series $x^{(1)}$ is generated using the series $x^{(0)}$.

$x^{(1)}(k) = \{10.6, 15.1, 22.4, 30, 37, ..., 701.5, 713.7\}$

These are used to estimate the parameters of *a* and *b*. The estimate values of *a* and *b* are 0.0000396 and 8.095 respectively.

The values of *a* and *b* are put into the Grey model and the following equation is obtained

$$\hat{x}_0^{(0)}(k) = [10.6 – (8.095/0.0000396)]*(1 – e^{0.0000396})*e^{-0.0000396(k-1)}$$

This equation is used to forecast the next 20 data which account for the last five years, for k = 89, 90, ..., 108.

Comparing the forecast results with the observed values in 'Sample 10', the MAE, MSE and RMSE are computed. Their values are 0.977, 1.740 and 1.319 respectively.

3.2.4. Grey method with Optimization of Background Value

The first thing to do is to estimate the value of parameter *a* using the following equation.

$$a(k) = \ln x^{(0)}(k) – \ln x^{(0)}(k-1)$$

For every value of k = 2,3,...,88 a new value of *a* is obtained and at the end, those values are averaged to obtain the final value of

a = Σa(k)/87 = 0,0016.

Next, the background value needs to be estimated for every value of k between [2, 88], namely $z^{(1)}(k)$.

After that, the parameter *b* needs to be estimated in its turn, for every single value of $z^{(1)}(k)$. The final estimate of *b* is the average of all the positive values of *b(k)* which is found to be

$$b = \frac{\sum positive(b(k))}{87-(7+21)} = 9.4.$$

Finally, using the values of *a*, *b* and $x^{(0)}$, the following Grey prediction model is obtained:

$$\hat{x}_0^{(0)}(k) = [x^{(0)}(1) – (b/a)]*(1 - e^{a})*e^{-a(k-1)} = [10.6 – (9.4/0.0016)]*(1 – e^{0,0016})*e^{-0.0016(k-1)}$$

Using this equation, the values for the next 20 periods, corresponding to the 4 quartiles of every successive year from 2012 through 2016, can be predicted for k values of 89, 90, 91, ..., 107, 108, respectively.

MAE, MSE and RMSE are found to be 0.99, 1.79 and 1.33, respectively.

4. RESULTS

Table 2 summarizes the results that different methods gave with the unemployment dataset, which was referred to as the initial dataset. A total of five algorithms were used. The dataset had a sample size of 27. Recall that the first twenty-two entries were used to set up the models for each of the six algorithms, and the last five entries were used to test the models and compute the errors. The estimators used for the error were the MAE, the MSE and the MRSE.

Table 2: Errors from the unemployment dataset

Methods	MAE	MSE	RMSE
Simple moving averages	0.8611	1.4619	1.20
Single exponential smoothing	0.146	0.046	0.214
GM(1,1)	1.068	1.3718	1.17
Grey prediction with rolling mechanism	1.512	2.99	1.729
Grey model with optimization of background value	0.4882	0.5087	0.71

The single exponential smoothing method has the lowest errors; this is because SES methods work very well with series which do not exhibit any trend or seasonal pattern. The data used in the experiment is a good example of such series. However, the Grey model with optimization of the background value has the second lowest errors. It outperforms both the original grey model GM(1,1) and the grey model with rolling mechanism.

A total of four methods were used on the bootstrap data or 'Sample 10'. The method of Grey prediction with rolling mechanism is very exhaustive with long-term forecasting. It is best used in short-term forecasting. In order to use it for long periods predictions, it is best to have it implemented in a software or develop a piece of coding and let a computer do the calculations if possible. Unfortunately, there is no code available for this method yet; therefore, it hasn't been used with the bootstrap dataset. Table 3 summarizes the errors obtained after the prediction operations of each of the five models.

Here again the SES performed better than all the other algorithms. It is so because the bootstrap series also doesn't exhibit any trend or seasonal pattern. The GM(1,1) and the Grey model with optimization of the background value have the second and third lowest errors. This time, the GM(1,1) performed slightly better than the Grey model with optimization of the background value, with a difference of only 0.02 in the MAE and 0.01 in the RMSE.

Table 3: Errors from the bootstrap dataset

Methods	MAE	MSE	RMSE
Simple moving averages	1.29	2.83	1.68
Single exponential smoothing	0.194	0.072	0.268
GM(1,1)	0.977	1.74	1.32
Grey model with optimization of the background value	0.99	1.79	1.33

5. CONCLUSION

The original grey method and the optimized model have proven to be good forecasting models for both datasets. Apart from the SES method, they performed better than every other algorithm. However, it is important to notice that since the grey equation has exponential factors, the values of the powers of each exponential term have a high impact in the prediction operations. Negative values of the parameter *a* will cause the predicted values to follow an upward trend, meaning that their values will increase over time, whereas positive values of the same parameter will cause the opposite effect. For long-term predictions, this situation can result in significant deviations of the predicted values from the observed ones. Therefore, it can be concluded that the grey models are more suitable for short-term predictions. The grey prediction with rolling mechanism (GPRM) is also best used in short-term predictions, since its methodology hasn't been implemented in any software program, yet. Furthermore, when working with the optimized grey model (the grey model with optimization of the background value) on the bootstrap data, another interesting thing was discovered. It was observed that successive entries of 'Sample 10' had sometimes the same value, for example quartile 1 and 2 of year 1997 both have an unemployment rate of 10,6. One aspect of the optimized model is that it has some division operations. The dividends are often the result of the subtraction of two successive entries, and since some of those entries have equal values, that result can be equal to zero sometimes. Therefore, any division by zero will give an undefined result. Such results were observed a few times during the application of the method. They have been discarded, meaning that they haven't been considered in the final averaging operation. Despite this issue, the method still gave very good results.

The principle of parsimony states that amongst a set of models, the one which is the simplest (simple in the number of parameters as well as in the application) should be chosen to work with (DeLurgio, 1998). Although the new ones performed well, it is best to choose methods such as the Simple Exponential Smoothing or the ARIMA or the Regression models which are easier to implement, unless being advised to. The heuristic models can be used if time and complexity are no issues for the forecaster. Further work needs to be done on the GPRM model because it has the potential to give very good forecasts, if its algorithm is implemented in a software. The same should be done with all the other heuristic methods discussed in this study as this will greatly help facilitate their use and thus raised them to a desired level of parsimony. It is also important to recall that they are mostly used with small size datasets (because of their complexity) and for short-term predictions. It would be interesting to use them with big datasets and see how they behave. This could reveal more about their potential and perhaps help increase their performances.

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