

Article

Fusing Nature with Computational Science for Optimal Signal Extraction

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Abstract: Fusing nature with computational science has been proved paramount importance and researchers have also shown growing enthusiasm on inventing and developing nature inspired algorithms for solving complex problems across subjects. Inevitably, these advancements have rapidly promoted the development of data science, where nature inspired algorithms are changing the traditional way of data processing. This paper proposes the hybrid approach, namely SSA-GA, which incorporates the optimization merits of genetic algorithm (GA) for the advancements of Singular Spectrum Analysis (SSA). This approach further boosts the performance of SSA forecasting via better and more efficient grouping. Given the performances of SSA-GA on 100 real time series data across various subjects, this newly proposed SSA-GA approach is proved to be computationally efficient and robust with improved forecasting performance.

Keywords: forecasting; Singular Spectrum Analysis; genetic algorithm



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1. Introduction

The vigorous advancements of data science and computational technologies recent decades have significantly altered the way of conducting interdisciplinary research. Meanwhile, these interdisciplinary developments have also injected novel aspects of thinking and problem solving capabilities back to the progression of computational algorithms. Scientists march on the path of seeking knowledge of everything we encounter in life and the nature, which itself acts as the most inclusive housing facility to all, always seems to have its wise answers. Just as the phrase “let nature take its course”, researchers also seek means to better appreciate the solutions nature may have to offer. It is not new that researchers invent and implement algorithms inspired by the nature as intelligent solution to complex problems and these achievements continuously bring new breakthroughs on a wider scale of science and technology. A recent review focusing on nature inspired algorithms can be found in [1]. Among which, some well established models include: the neural networks [2], which was inspired by the mechanism of biological neural networks, and has been widely applied and developed to form a large branch containing various types of computational architectures; swarm intelligence (SI) [3,4], which has been contributing to the intelligent advancements on both scientific and engineering domains, and a wide spectrum of SI inspired algorithms (i.e., bat algorithm, ant colony optimization, firefly algorithm, etc.) have emerged recent decades [1]; genetic algorithm (GA) [5], which was inspired by the theory of natural evolution, has promoted the trends of evolutionary algorithms and been widely applied for searching and optimization. The list of nature inspired algorithms goes on and new ones are developed and update the list regularly, we are not intended to review all here, but the wide scale of developments and implementations certainly reflected the significance of seeking knowledge via the mysterious means offered by nature.

Among the various branches of nature inspired algorithms, this paper focuses on GA, the one that shows extraordinary performance in optimization [1]. In brief, GA simulates the optimization process for computational problems in line with the process of natural evolution [5]. Optimal solution thus can be considered as the evolutionary outcome via mutation, crossover and selection by fitness evaluation. This algorithm is widely applicable considering the common existence of optimization problem in computational science. There have been a collection of review papers that investigate various implementation of GA in different subjects, such as chemometrics [6], electromagnetics [7], mechanical engineering [8], image reconstruction [9], production and operations management [10], supply chain management [11], economics and finance [12], etc. Moreover, there are also numerous attempts of researchers, who applied GA alone or in combination with other algorithms so to seek better solutions for specific problems. The applications of GA are rather diverse that, to the best of our knowledge, no research alone has reviewed them all.

In regard to the domain of signal extraction and forecasting, GA has certainly played an active role in the recent decades. Some of the selected topics include: bankruptcy prediction [13–15], credit scoring [16,17], crude oil price [18–20], tourism demand [21–23], the beta systematic risk [24], financial data [25,26], gas demand [27], electric load [28,29], wind speed [30], rainfall [31], etc. Via comprehensively exploring existing literature, it came to our attention that although GA has been applied jointly with many data analytics techniques in practice, to name a few, neural network, principal component analysis, wavelet analysis, long and short memory network, support vector machines. To the best of our knowledge, it has not been exploited jointly with Singular Spectrum Analysis (SSA) [32], which is a powerful technique for time series analysis and has been widely applied for denoising, signal extraction and forecasting [33–36].

Given the rapid development of SSA and its hybrid approaches [35,37–40], this is not the first attempt of collaborating SSA with nature inspired algorithms. There has been a successful journey full of advancements and one of the most popular collaborator is neural network. Different sub-branches of neural network have been fused with SSA for achieving better forecasting, for instance, fuzzy/Elman/Laguerre neural network and SSA are combined for wind speed forecasting in [41–43], for road traffic forecasting in [44], for energy demand/load forecasting in [45], for water demand forecasting in [46], etc. The authors have proposed the Colonial Theory (CT) inspired SSA-CT approach back in [35], which incorporates CT for an improved “grouping” process of basic SSA. Moreover, the authors also explored the hybrid approach of SSA and neural network for improving the prediction of tourism demand in [40]. This paper serves as a further development of [35] via implementing GA for efficiently optimising of the “grouping” stage of basic SSA so to achieve improved forecasting. It is also of note that this paper contributes to the literature where for the first time to the best of our knowledge, SSA and GA are jointly collaborated for forecasting advancements. Furthermore, in order to provide robust validation of this newly proposed approach and reveal its true performance in forecasting, 100 real time series from various subjects are considered in this paper.

The remainder of the paper is organized as follows: Section 2 demonstrates the basic SSA and CT inspired SSA-CT [35] processes. Section 3 introduces the newly proposed SSA-GA approach which was developed incorporating the advanced features of GA. Section 4 adopted 100 real time series data across various subjects of research for evaluating the forecasting performance of SSA-GA in comparison with the basic SSA. Finally, the paper concludes in Section 5.

2. Basic SSA and SSA-CT

According to [32], the basic SSA contains two stages: Decomposition and Reconstruction, while each stage includes its own two steps, Embedding and Singular Value Decomposition (SVD), and Grouping and Diagonal Averaging, respectively. To conduct this process, two setting options will need to be decided: the window length L and number of eigenvalues r . It is of note that the detailed instructions of SSA can be found in [32], which

will not be reproduced here. Instead, a brief summary of the process will be presented below and we mainly follow [35].

For the Decomposition stage, with a selected window length L , the one dimensional main time series can then be embedded into a multi-dimensional variable, which forms a trajectory matrix, this is then followed by SVD, where a group of small number of independent and interpretable components are achieved. Second stage, namely Reconstruction, starts from the important step—“grouping”. Briefly to say, this step aims to gather eigenvalues of different characters, i.e., trend, seasonality, etc., whilst leaving out those corresponding to noise. Lastly, the grouped eigenvalues will then be transformed back to a one dimensional time series, namely the signal, via performing diagonal averaging.

A common technique in SSA’s grouping stage is to choose first r components to reconstruct the signal. The number of components is selected to minimize in-sample Root Mean Square Error (RMSE) or out-of-sample forecasting RMSE. Selecting the first r components to reconstruct the signal comes from the common believe that later components are related noise in time series, since they have smaller variances and higher frequencies.

Hassani et al. (2016) [35] proposed an alternative approach, namely SSA-CT, which is inspired by CT. They showed that using first r components to reconstruct the signal does not necessarily produce the minimum RMSE results. SSA-CT considers all possible 2^L combination of components, for a given window length L , to reconstruct the signal. Then it uses the combination of components which produce minimum RMSE results. Although SSA-CT can improve the basic SSA’s results, checking all 2^L possible combinations of components to find the minimum RMSE is computationally expensive and time consuming.

3. SSA-GA

Consider the non zero real valued time series $\{y_t\}_1^N$. If the aim is to extract the signal from noise, all available data will be used to calculate the RMSE. If the main aim is to forecast the time series, one may divide the series in to two parts, use the first part (say $\frac{2}{3}$ of the data) to find the minimum RMSE grouping (training data) and use the rest of the series to test the out-of-sample forecasting performance (as RMSE of the second part). The SSA-GA follows these steps:

1. Run a basic SSA on training data and find the optimum r .
2. Use the training data to build the trajectory matrix $\mathbf{X} = (x_{ij})_{i,j=1}^{L,K} = [X_1, \dots, X_k]$ where $X_j = (y_j, \dots, y_{L+j-1})^T$.
3. Apply the SVD for \mathbf{X} and calculate eigenvalues $\lambda_1 \geq \dots \geq \lambda_L$ and corresponding eigenvectors U_1, \dots, U_L . Obtain $V_i = \mathbf{X}^T U_i / \sqrt{\lambda_i}$ and $\mathbf{X}_i = \sqrt{\lambda_i} U_i V_i^T$.
4. Define a chromosome C_i as a vector of length L with binary values:

$$C_i = (c_{i1}, c_{i2}, \dots, c_{iL}),$$

where $c_{ij} = 1$ if j th components is considered for signal reconstruction and $c_{ij} = 0$, otherwise.

5. Build a population containing M chromosomes, i.e., chromosomes C_1, \dots, C_M . Generate $K\%$ ($K > 70$) of the chromosomes in the population randomly (from uniform distribution). This will produce chromosomes C_1 to C_k . Add $C_{k+1} = (0, 0, \dots, 0)$ and $C_{k+2} = (1, 1, \dots, 1)$ to the population (as extreme solutions). The rest of the population will be the same chromosomes as the basic SSA solution:

$$c_{ij} = \begin{cases} 1 & j \leq r \\ 0 & j > r \end{cases} \quad i = k+3, \dots, M,$$

where r is the grouping parameter from basic SSA (step 1).

6. Use a binary crossover function to produce M' offspring chromosomes. A simple crossover function produce offspring chromosomes as follows:
 - (a) Pair chromosomes in the population randomly.

- (b) For a given pair of chromosomes C_i and C_j generate random number d from uniform distribution ($1 \leq d \leq L$).
- (c) Produce offspring chromosomes for C_i and C_j with switching their first d genes:

$$\text{First offspring} = (c_{i1}, \dots, c_{id}, c_{j(d+1)}, \dots, c_{jL})$$

$$\text{Second offspring} = (c_{j1}, \dots, c_{jd}, c_{i(d+1)}, \dots, c_{iL})$$

7. Produce weight matrix \mathbf{W}_i for each of $M + M'$ chromosomes:

$$\mathbf{W}_i = \text{diag}(C_i), \quad i = 1, \dots, M + M'.$$

8. Reconstruct the signal for each weight matrix \mathbf{W}_i :

$$\hat{\mathbf{S}}_i = \mathbf{U}_1(\mathbf{W}_i \Sigma_1) \mathbf{V}_1^T, \quad i = 1, \dots, M + M'.$$

9. For each chromosomes generate in-sample h step ahead forecasting and calculate the in-sample RMSE for all $M + M'$ chromosomes. Select the M chromosomes with smallest RMSE as the new population.
10. Repeat steps 6 to 9 until minimum RMSE in the population does not improve for several iterations.
11. Begin with $L = 2$ and repeat steps 1 to 10 for $2 \leq L \leq \frac{N}{2}$, to find the L and grouping parameter which minimizes in-sample RMSE.

Adding basic SSA solution to the initial population, in step 5, will boost the searching speed and grants that the final grouping solution will be at least as accurate as basic SSA. The SSA-GA as described above, will expedite SSA-CT's searching for minimum RMSE solution and grants that the final solution is at least as good as basic SSA, in the same time. Although, it should be mentioned that the minimum in sample RMSE does not necessarily grants minimum out-of-sample RMSE.

4. Empirical Results

We used a set of 100 real time series, with different sampling frequencies, normality, stationarity and skewness characteristics, to compare the accuracy of SSA-GA with basic SSA. The dataset is accessed through Data Market (<http://datamarket.com> (accessed on 12 January 2021)) and previously was employed by Ghodsi et al. [47] and Hassane et al. [36] to compare different SSA based forecasting methods. Table 1 shows description of each time series in the dataset. The name and description of each time series and their codes assigned to improve presentation are presented in Table A1 in Appendix A. Table A2 presents descriptive statistics for all time series to enable the reader to obtain a rich understanding of the nature of the real data. This also includes skewness statistics, results from the normality (Shapiro-Wilk) and stationarity (Augmented Dickey-Fuller) tests. As it can be seen the data comes from different fields of energy, finance, health, tourism, housing market, crime, agriculture, economics, chemistry, ecology, and production, to name a few. Figure 1 shows a selection of 9/100 series used in this study.

Table 1. Number of time series with each feature.

Factor	Levels					
	Sampling Frequency	Annual 5	Monthly 83	Quarterly 4	Weekly 4	Daily 2
Skewness	Positive Skew 61		Negative Skew 21		Symmetric 18	
Normality	Normal 18			Non-normal 82		
Stationarity	Stationary 14			Non-Stationary 86		

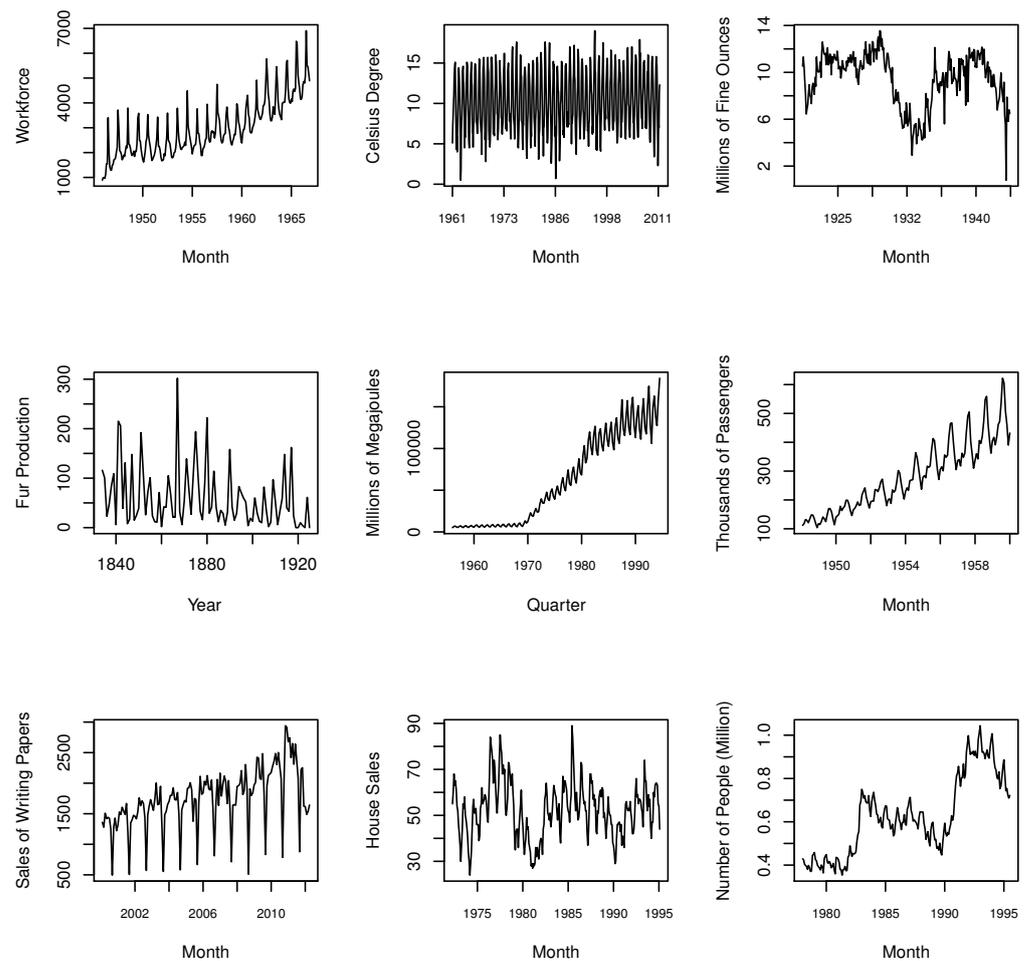


Figure 1. A selection of nine real time series.

For each time series, the out-of-sample forecasting RMSE is calculated using both basic SSA and SSA-GA, for very short, short, long and very long term forecasting horizons (i.e., $h = 1, 3, 6, 12$). To compare the RMSEs from two methods, we used the RRMSE defined as ratio of SSA-GA's RMSE to basic SSA's RMSE (i.e., $RRMSE = RMSE_{SSA-GA} / RMSE_{basicSSA}$). We also employed Kolmogorov-Smirnov Predictive Accuracy (KSPA) test [48] to compare the accuracy of two methods. Table A3 shows the RRMSEs and p -values for KSPA test, for each time series. Descriptions of RRMSEs are given in Table 2. As it can be seen, the SSA-GA's results are not necessarily same as the basic SSA's. As mentioned before, the SSA-GA's in-sample RMSE is always at least as good as basic SSA. However, in-sample accuracy does not guarantee out-of sample accuracy. This means in all the cases that the SSA-GA's result differs from basic SSA, it has better accuracy for in-sample forecasting. However, as it is evident from Table 2, it doesn't necessarily improve out-of-sample forecasting accuracy. Figure 2 shows that the mode of RRMSEs in these 100 case is less than 1 for all forecasting horizons. According to the results given in Table 2 and Figure 2, SSA-GA and basic SSA does not dominate each other in out-of-sample forecasting accuracy. This could be the result of over-fitting in SSA-GA, since SSA-GA is always at least as accurate as basic SSA for in-sample forecasting.

Table 2. RRMSEs’ descriptives and Krskal-Wallis test results.

		Forecasting Horizon			
		h = 1	h = 3	h = 6	h = 12
	RRMSE’s Median	1.0618	1.0362	1.0319	1.0302
	N. RRMSE < 1 ¹	21	24	21	24
	N. RRMSE > 1 ²	57	54	57	54
	N. RRMSE < 1 (Significantly) ³	3	5	4	6
	N. RRMSE > 1 (Significantly) ³	17	13	7	14
Kruskal-Wallis <i>p</i> -value’s	RRMSE ~ Frequency ⁴	0.1975	0.1975	0.1975	0.1975
	RRMSE ~ Normality ⁴	0.9047	0.9047	0.9047	0.9047
	RRMSE ~ Stationarity ⁴	0.1625	0.1625	0.1625	0.1625
	RRMSE ~ Skewness ⁴	0.9618	0.9618	0.9618	0.9618

¹ Number of RRMSEs less than 1; ² Number of RRMSEs larger than 1; ³ Cases with KSPA’s *p*-value less than 0.05; ⁴ Kruskal-Wallis’ *p*-value for testing the effect of given factor on RRMSE.

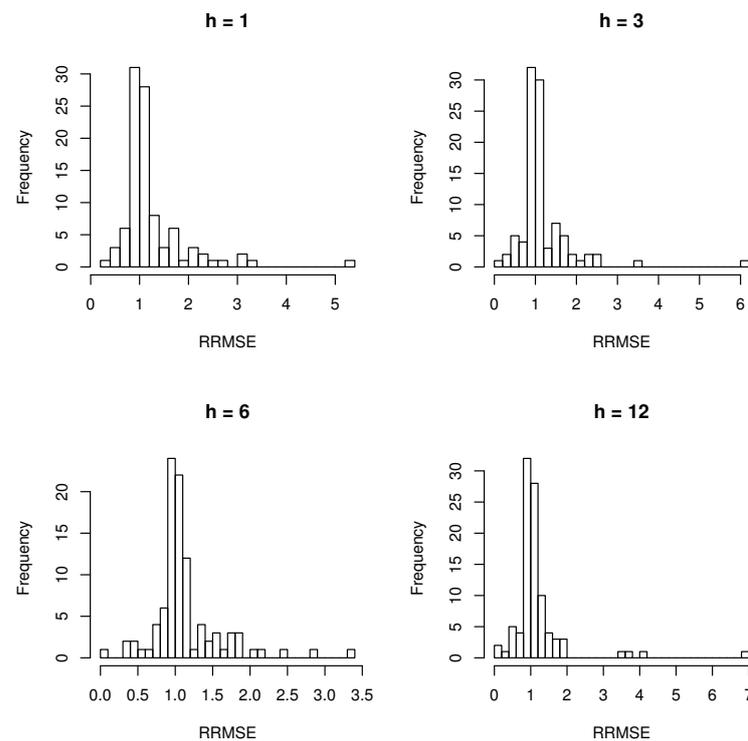


Figure 2. Histogram of RRMSEs for different forecasting horizons (To better illustrate the data, one extreme value is removed for h = 6 and two extreme values are removed for h = 12).

In order to further investigate the accuracy of SSA-GA in forecasting time series with different characteristics, Kruskal-Wallis test is employed to compare the RRMSE of time series with different features. The Kruskal-Wallis test results are given in Table 2. As Kruskal-Wallis test results show, the sampling frequency, stationarity, normality and skewness of time series does not affect RRMSE significantly. In other words, the difference between accuracy of SSA-GA and basic SSA is not affected by these factors. According to these results, although SSA-GA has better in-sample forecasting accuracy, it may have overfitting issue for out of sample forecasting. Nevertheless, using SSA-GA, as an advanced version of SSA-CT, can improve the basic SSA’s results and at the same time will reduce SSA-CT’s computational expenses.

5. Conclusions

Nature inspired algorithms have shown remarkable performance in solving complex problems that traditional computational approaches fail or struggle to achieve. As evident by the various achievements of nature inspired algorithms across subjects in searching, forecasting, optimising, and signal extracting. The ones which better appreciate the means of nature tend to better understand the natural mechanism that holds underlying the

broad scale of science and technology. Given the emerging trends of fusing nature with computational science for the past decades, this paper aims to have SSA and GA joint forces so to achieve more efficient and accurate forecast.

To the best of our knowledge, this paper is the first research that combines the powerful time series analysis technique SSA with the widely applied and established GA. This research also progresses in line with the paper [35], in which the authors proposed the hybrid SSA-CT technique that employed CT for improving the grouping stage of basic SSA. As a developed version, SSA-GA is introduced so that the merits of optimization feature of GA is adopted for further improving the efficiency of grouping and optimizing the signal reconstruction. The performance of this newly proposed hybrid approach is verified by a collection of 100 time series covering a range of diverse subjects, also promising results are achieved, especially for the in sample reconstruction. To clearly demonstrate the comparison and critically evaluate the performance, the authors employed RMSE, RRMSE, KSPA test and Kruskal-Wallis test, so to give a comprehensive investigation of SSA-GA in comparison with basic SSA. In general, with much improved SSA-CT's computational efficiency and better grouping process, the signal reconstruction has been significantly improved, while the out of sample forecasting shows stable performance which is robust as SSA-CT. Considering that basic SSA has already been a powerful tool in reconstruction and forecasting with outstanding performance, even small improvement and efficiency boost can indicate huge steps in terms of processing data in scale. It is recognised that the potential over fitting issue with out of sample and this will be one direction to address for our future research. Advanced versions of nature inspired algorithms could be explored alone or jointly to further improve part or more stages of SSA, as well as multivariate SSA.

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Appendix A

Table A1. List of 100 real time series.

Code	Name of Time Series
A001	US Economic Statistics: Capacity Utilization.
A002	Births by months 1853–2012.
A003	Electricity: electricity net generation: total (all sectors).
A004	Energy prices: average retail prices of electricity.
A005	Coloured fox fur returns, Hopedale, Labrador, 1834–1925.
A006	Alcohol demand (log spirits consumption per head), UK, 1870–1938.
A007	Monthly Sutter county workforce, January 1946–December 1966 priesema (1979).
A008	Exchange rates—monthly data: Japanese yen.
A009	Exchange rates—monthly data: Pound sterling.
A010	Exchange rates—monthly data: Romanian leu.
A011	HICP (2005 = 100)—monthly data (annual rate of change): European Union (27 countries).
A012	HICP (2005 = 100)—monthly data (annual rate of change): UK.
A013	HICP (2005 = 100)—monthly data (annual rate of change): US.
A014	New Homes Sold in the United States.
A015	Goods, Value of Exports for United States.

Table A1. Cont.

Code	Name of Time Series
A016	Goods, Value of Imports for United States.
A017	Market capitalisation—monthly data: UK.
A018	Market capitalisation—monthly data: US.
A019	Average monthly temperatures across the world (1701–2011): Bournemouth.
A020	Average monthly temperatures across the world (1701–2011): Eskdalemuir.
A021	Average monthly temperatures across the world (1701–2011): Lerwick.
A022	Average monthly temperatures across the world (1701–2011): Valley.
A023	Average monthly temperatures across the world (1701–2011): Death Valley.
A024	US Economic Statistics: Personal Savings Rate.
A025	Economic Policy Uncertainty Index for United States (Monthly Data).
A026	Coal Production, Total for Germany.
A027	Coke, Beehive Production (by Statistical Area).
A028	Monthly champagne sales (in 1000's) (p. 273: Montgomery: Fore. and T.S.).
A029	Domestic Auto Production.
A030	Index of Cotton Textile Production for France.
A031	Index of Production of Chemical Products (by Statistical Area).
A032	Index of Production of Leather Products (by Statistical Area).
A033	Index of Production of Metal Products (by Statistical Area).
A034	Index of Production of Mineral Fuels (by Statistical Area).
A035	Industrial Production Index.
A036	Knit Underwear Production (by Statistical Area).
A037	Lubricants Production for United States.
A038	Silver Production for United States.
A039	Slab Zinc Production (by Statistical Area).
A040	Annual domestic sales and advertising of Lydia E, Pinkham Medicine, 1907 to 1960.
A041	Chemical concentration readings.
A042	Monthly Boston armed robberies January 1966–October 1975 Deutsch and Alt (1977).
A043	Monthly Minneapolis public drunkenness intakes January '66–July '78.
A044	Motor vehicles engines and parts/CPI, Canada, 1976–1991.
A045	Methane input into gas furnace: cu. ft/min. Sampling interval 9 s.
A046	Monthly civilian population of Australia: thousand persons. February 1978–April 1991.
A047	Daily total female births in California, 1959.
A048	Annual immigration into the United States: thousands. 1820–1962.
A049	Monthly New York City births: unknown scale. January 1946–December 1959.
A050	Estimated quarterly resident population of Australia: thousand persons.
A051	Annual Swedish population rates (1000's) 1750–1849 Thomas (1940).
A052	Industry sales for printing and writing paper (in Thousands of French francs).
A053	Coloured fox fur production, Hebron, Labrador, 1834–1925.
A054	Coloured fox fur production, Nain, Labrador, 1834–1925.
A055	Coloured fox fur production, oak, Labrador, 1834–1925.
A056	Monthly average daily calls to directory assistance January '62–December '76.
A057	Monthly Av. residential electricity usage Iowa city 1971–1979.
A058	Monthly av. residential gas usage Iowa (cubic feet)*100 '71–'79.
A059	Monthly precipitation (in mm), January 1983–April 1994. London, United Kingdom .
A060	Monthly water usage (mL/day), London Ontario, 1966–1988.
A061	Quarterly production of Gas in Australia: million megajoules. Includes natural gas from July 1989. March 1956–September 1994.
A062	Residential water consumption, January 1983–April 1994. London, United Kingdom.
A063	The total generation of electricity by the U.S. electric industry (monthly data for the period January 1985–October 1996).
A064	Total number of water consumers, January 1983–April 1994. London, United Kingdom.
A065	Monthly milk production: pounds per cow. January 62–December 75.
A066	Monthly milk production: pounds per cow. January 62–December 75, adjusted for month length.
A067	Monthly total number of pigs slaughtered in Victoria. January 1980–August 1995.
A068	Monthly demand repair parts large/heavy equip. Iowa 1972–1979.
A069	Number of deaths and serious injuries in UK road accidents each month. January 1969–December 1984.
A070	Passenger miles (Mil) flown domestic U.K. July '62–May '72.
A071	Monthly hotel occupied room av. '63–'76 B.L.Bowerman et al.

Table A1. Cont.

Code	Name of Time Series
A072	Weekday bus ridership, Iowa city, Iowa (monthly averages).
A073	Portland Oregon average monthly bus ridership (/100).
A074	U.S. airlines: monthly aircraft miles flown (Millions) 1963–1970.
A075	International airline passengers: monthly totals in thousands. January 49–December 60.
A076	Sales: souvenir shop at a beach resort town in Queensland, Australia. January 1987–December 1993.
A077	Der Stern: Weekly sales of wholesalers A, '71–'72.
A078	Der Stern: Weekly sales of wholesalers B, '71–'72'
A079	Der Stern: Weekly sales of wholesalers '71–'72.
A080	Monthly sales of U.S. houses (thousands) 1965–1975.
A081	CFE specialty writing papers monthly sales.
A082	Monthly sales of new one-family houses sold in USA since 1973.
A083	Wisconsin employment time series, food and kindred products, January 1961–October 1975.
A084	Monthly gasoline demand Ontario gallon millions 1960–1975.
A085	Wisconsin employment time series, fabricated metals, January 1961–October 1975.
A086	Monthly employees wholes./retail Wisconsin '61–'75 R.B.Miller.
A087	US monthly sales of chemical related products. January 1971–December 1991.
A088	US monthly sales of coal related products. January 1971–December 1991.
A089	US monthly sales of petrol related products. January 1971–December 1991.
A090	US monthly sales of vehicle related products. January 1971–December 1991.
A091	Civilian labour force in Australia each month: thousands of persons. February 1978–August 1995.
A092	Numbers on Unemployment Benefits in Australia: monthly January 1956–July 1992.
A093	Monthly Canadian total unemployment figures (thousands) 1956–1975.
A094	Monthly number of unemployed persons in Australia: thousands. February 1978–April 1991.
A095	Monthly U.S. female (20 years and over) unemployment figures 1948–1981.
A096	Monthly U.S. female (16–19 years) unemployment figures (thousands) 1948–1981.
A097	Monthly unemployment figures in West Germany 1948–1980.
A098	Monthly U.S. male (20 years and over) unemployment figures 1948–1981.
A099	Wisconsin employment time series, transportation equipment, January 1961–October 1975.
A100	Monthly U.S. male (16–19 years) unemployment figures (thousands) 1948–1981.

Table A2. Descriptives for the 100 time series.

Code	F	N	Mean	Med.	SD	CV	Skew.	SW(p)	ADF	Code	F	N	Mean	Med.	SD	CV	Skew.	SW(p)	ADF
A001	M	539	80	80	5	6	-0.55	<0.01	-0.60 [†]	A002	M	1920	271	249	88	33	0.16	<0.01	-1.82 [†]
A003	M	484	2.59 × 10 ⁵	2.61 × 10 ⁵	6.88 × 10 ⁵	27	0.15	<0.01	-0.90 [†]	A004	M	310	7	7	2	28	-0.24	<0.01	0.56 [†]
A005	D	92	47.63	31.00	47.33	99.36	2.27	<0.01	-3.16	A006	Q	207	1.95	1.98	0.25	12.78	-0.58	<0.01	0.46 [†]
A007	M	252	2978	2741	1111	37.32	0.79	<0.01	-0.80 [†]	A008	M	160	128	128	19	15	0.34	<0.01	-0.59 [†]
A009	M	160	0.72	0.69	0.10	13	0.66	<0.01	0.53 [†]	A010	M	160	3.41	3.61	0.83	24	-0.92	<0.01	1.58 [†]
A011	M	201	4.7	2.6	5.0	106	2.24	<0.01	-2.66	A012	M	199	2.1	1.9	1.0	49	0.92	<0.01	-0.79 [†]
A013	M	176	2.5	2.4	1.6	66	-0.52	<0.01	-2.27 [†]	A014	M	606	55	53	20	35	0.79	<0.01	-1.41 [†]
A015	M	672	3.39	1.89	3.48	103	1.09	<0.01	2.46 [†]	A016	M	672	5.18	2.89	5.78	111	1.13	<0.01	1.91 [†]
A017	M	249	130	130	24	19	0.35	<0.01	0.24 [†]	A018	M	249	112	114	25	22	-0.01	0.01*	0.06 [†]
A019	M	605	10.1	9.6	4.5	44	0.05	<0.01	-4.77	A020	M	605	7.3	6.9	4.3	59	0.04	<0.01	-6.07
A021	M	605	7.2	6.8	3.3	46	0.13	<0.01	-4.93	A022	M	605	10.3	9.9	3.8	37	0.04	<0.01	-4.19
A023	M	605	24	24	10	40	-0.02	<0.01	-7.15	A024	M	636	6.9	7.4	2.6	38	-0.29	<0.01	-1.18 [†]
A025	M	343	108	100	33	30	0.99	<0.01	-1.23 [†]	A026	M	277	11.7	11.9	2.3	20	-0.16	0.06*	-0.40 [†]
A027	M	171	0.21	0.13	0.19	88	1.26	<0.01	-1.81 [†]	A028	M	96	4801	4084	2640	54.99	1.55	<0.01	-1.66 [†]
A029	M	248	391	385	116	30	-0.03	0.08*	-1.22 [†]	A030	M	139	89	92	12	13	-0.82	<0.01	-0.28 [†]
A031	M	121	134	138	27	20	0.05	<0.01	1.51 [†]	A032	M	153	113	114	10	9	-0.29	0.45*	-0.52 [†]
A033	M	115	117	118	17	15	-0.29	0.03*	-0.46 [†]	A034	M	115	110	111	11	10	-0.53	0.02*	0.30 [†]
A035	M	1137	40	34	31	78	0.56	<0.01	5.14 [†]	A036	M	165	1.08	1.10	0.20	18.37	-1.15	<0.01	-0.59 [†]
A037	M	479	3.04	2.83	1.02	33.60	0.46	<0.01	0.61 [†]	A038	M	283	9.39	10.02	2.27	24.15	-0.80	<0.01	-1.01 [†]
A039	M	452	54	52	19	36	-0.15	<0.01	0.08 [†]	A040	Q	108	1382	1206	684	49.55	0.83	<0.01	-0.80 [†]
A041	H	197	17.06	17.00	0.39	2.34	0.15	0.21*	0.09 [†]	A042	M	118	196.3	166.0	128.0	65.2	0.45	<0.01	0.41 [†]
A043	M	151	391.1	267.0	237.49	60.72	0.43	<0.01	-1.17 [†]	A044	M	188	1344	1425	479.1	35.6	-0.41	<0.01	-1.28 [†]
A045	H	296	-0.05	0.00	1.07	-1887	-0.05	0.55*	-7.66	A046	M	159	11,890	11,830	882.93	7.42	0.12	<0.01	5.71
A047	D	365	41.98	42.00	7.34	17.50	0.44	<0.01	-1.07 [†]	A048	A	143	2.5 × 10 ⁵	2.2 × 10 ⁵	2.1 × 10 ⁵	83.19	1.06	<0.01	-2.63
A049	M	168	25.05	24.95	2.31	9.25	-0.02	0.02*	0.07 [†]	A050	Q	89	15,274	15,184	1358	8.89	0.19	<0.01	9.72 [†]
A051	A	100	6.69	7.50	5.88	87.87	-2.45	<0.01	-3.06	A052	M	120	713	733	174	24.39	-1.09	<0.01	-0.78 [†]
A053	A	91	81.58	46.00	102.07	125.11	2.80	<0.01	-3.44	A054	A	91	101.80	77.00	92.14	90.51	1.43	<0.01	-3.38
A055	A	91	59.45	39.00	60.42	101.63	1.56	<0.01	-3.99	A056	M	180	492.50	521.50	189.54	38.48	-0.17	<0.01	-0.65 [†]
A057	M	106	489.73	465.00	93.34	19.06	0.92	<0.01	-1.21 [†]	A058	M	106	124.71	94.50	84.15	67.48	0.52	<0.01	-3.88
A059	M	136	85.66	80.25	37.54	43.83	0.91	<0.01	-1.88 [†]	A060	M	276	118.61	115.63	26.39	22.24	0.86	<0.01	-0.47 [†]
A061	Q	155	61,728	47,976	53,907	87.33	0.44	<0.01	0.06 [†]	A062	M	136	5.72 × 10 ⁷	5.53 × 10 ⁷	1.2 × 10 ⁷	21.51	1.13	<0.01	-0.84 [†]
A063	M	142	231.09	226.73	24.37	10.55	0.52	0.01	-0.39 [†]	A064	M	136	31,388	31,251	3232	10.30	0.25	0.22*	-0.16 [†]
A065	M	156	754.71	761.00	102.20	13.54	0.01	0.04*	0.04 [†]	A066	M	156	746.49	749.15	98.59	13.21	0.08	0.04*	-0.38 [†]
A067	M	188	90,640	91,661	13,926	15.36	-0.38	0.01*	-0.38 [†]	A068	M	94	1540	1532	474.35	30.79	0.38	0.05*	0.54 [†]
A069	M	192	1670	1631	289.61	17.34	0.53	<0.01	-0.74 [†]	A070	M	119	91.09	86.20	32.80	36.01	0.34	<0.01	-1.93 [†]
A071	M	168	722.30	709.50	142.66	19.75	0.72	<0.01	-0.52 [†]	A072	W	136	5913	5500	1784	30.17	0.67	<0.01	-0.68 [†]
A073	M	114	1120	1158	270.89	24.17	-0.37	<0.01	0.76 [†]	A074	M	96	10,385	10,401	2202	21.21	0.33	0.18*	-0.13 [†]
A075	M	144	280.30	265.50	119.97	42.80	0.57	<0.01	-0.35 [†]	A076	M	84	14,315	8771	15,748	110	3.37	<0.01	-0.29 [†]
A077	W	104	11,909	11,640	1231	10.34	0.60	<0.01	-0.16 [†]	A078	W	104	74,636	73,600	4737	6.35	0.64	<0.01	-0.59 [†]
A079	W	104	1020	1012	71.78	7.03	0.60	0.01*	-0.41 [†]	A080	M	132	45.36	44.00	10.38	22.88	0.17	0.15*	-0.81 [†]
A081	M	147	1745	1730	479.52	27.47	-0.39	<0.01	-1.15 [†]	A082	M	275	52.29	53.00	11.94	22.83	0.18	0.13*	-1.30 [†]

Table A2. Cont.

Code	F	N	Mean	Med.	SD	CV	Skew.	SW(p)	ADF	Code	F	N	Mean	Med.	SD	CV	Skew.	SW(p)	ADF
A083	M	178	58.79	55.80	6.68	11.36	0.93	<0.01	-0.92 [†]	A084	M	192	1.62×10^5	1.57×10^5	41,661	25.71	0.32	<0.01	0.25 [†]
A085	M	178	40.97	41.50	5.11	12.47	-0.07	<0.01	1.45 [†]	A086	M	178	307.56	308.35	46.76	15.20	0.17	<0.01	1.51 [†]
A087	M	252	13.70	14.08	6.13	44.73	0.16	<0.01	1.13 [†]	A088	M	252	65.67	68.20	14.25	21.70	-0.53	<0.01	-0.53 [†]
A089	M	252	10.76	10.92	5.11	47.50	-0.19	<0.01	-0.05 [†]	A090	M	252	11.74	11.05	5.11	43.54	0.38	<0.01	-0.88 [†]
A091	M	211	7661	7621	819	10.70	0.03	<0.01	3.27 [†]	A092	M	439	2.21×10^5	5.67×10^4	2.35×10^5	106.32	0.77	<0.01	1.61 [†]
A093	M	240	413.28	396.50	152.84	36.98	0.36	<0.01	-1.60 [†]	A094	M	211	6787	6528	604.62	8.91	0.56	<0.01	2.69 [†]
A095	M	408	1373	1132	686.05	49.96	0.91	<0.01	0.60 [†]	A096	M	408	422.38	342.00	252.86	59.87	0.65	<0.01	-1.95 [†]
A097	M	396	7.14×10^5	5.57×10^5	5.64×10^5	78.97	0.79	<0.01	-2.51 [†]	A098	M	408	1937	1825	794	41.04	0.64	<0.01	-1.15 [†]
A099	M	178	40.60	40.50	4.95	12.19	-0.65	<0.01	-0.10 [†]	A100	M	408	520.28	425.50	261.22	50.21	0.64	<0.01	-1.65 [†]

Note: * indicates data is normally distributed based on a Shapiro-Wilk test at $p = 0.01$. [†] indicates a nonstationary time series based on the Augmented Dickey-Fuller test at $p = 0.01$. A indicates annual, M indicates monthly, Q indicates quarterly, W indicates weekly, D indicates daily and H indicates hourly. N indicates series length.

Table A3. RRMSEs and KSPA p -values for the 100 time series.

Series' Code	Forecasting Horizon							
	h = 1		h = 3		h = 6		h = 12	
	RRMSE	KSPA p -Value	RRMSE	KSPA p -Value	RRMSE	KSPA p -Value	RRMSE	KSPA p -Value
A001	0.567	0.001	0.425	0.000	0.396	0.000	0.374	0.000
A002	1.297	0.001	1.347	0.000	1.358	0.000	1.359	0.000
A003	1.263	0.141	1.090	0.454	1.034	0.385	1.032	0.408
A004	1.632	0.017	0.543	0.012	0.547	0.105	0.572	0.391
A005	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A006	1.088	0.797	1.075	0.928	1.113	0.694	1.067	0.604
A007	2.015	0.092	2.452	0.026	3.339	0.162	667.713	0.042
A008	1.716	0.306	1.885	0.948	2.483	0.161	6.844	0.445
A009	0.976	1.000	0.969	0.948	0.966	0.997	0.973	1.000
A010	1.245	0.306	0.952	0.480	0.968	0.522	0.989	0.315
A011	0.669	0.231	0.371	0.068	0.427	0.050	0.616	0.043
A012	1.021	0.981	1.014	0.999	1.008	1.000	1.007	0.993
A013	1.027	1.000	1.010	1.000	1.008	1.000	1.010	0.999
A014	1.298	0.125	1.069	0.371	1.161	0.169	1.243	0.182
A015	2.259	0.000	1.663	0.000	1.121	0.114	0.901	0.000
A016	1.214	0.888	1.151	1.000	1.126	0.896	1.161	0.774
A017	0.614	0.132	0.587	0.063	0.672	0.414	0.700	0.717
A018	1.172	0.631	0.878	0.512	1.032	0.804	1.032	0.717
A019	1.021	0.518	1.012	0.254	1.030	0.534	1.025	0.870
A020	1.049	0.957	1.064	0.693	1.082	0.456	1.100	0.720
A021	1.117	0.984	1.154	0.524	1.148	0.383	1.141	0.720
A022	1.125	0.439	1.080	0.852	1.067	0.961	1.060	0.870
A023	1.135	0.518	1.150	0.374	1.158	0.319	1.128	0.720
A024	1.520	0.001	1.544	0.001	1.576	0.000	1.607	0.000
A025	1.796	0.003	1.729	0.002	1.661	0.006	1.796	0.000
A026	2.339	0.015	1.571	0.935	1.121	0.616	1.071	0.658
A027	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A028	1.081	0.987	1.054	0.422	1.062	0.501	1.072	0.160
A029	1.059	0.777	1.059	0.791	1.059	0.915	1.051	0.844
A030	1.627	0.707	6.047	0.545	49.035	0.420	3160.646	0.008
A031	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A032	1.172	0.919	1.103	0.791	1.208	0.653	1.453	0.562
A033	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A034	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A035	3.019	0.000	1.910	0.007	1.503	0.075	1.228	0.186
A036	1.079	0.994	1.083	0.996	1.062	0.964	1.061	0.979
A037	1.563	0.043	1.709	0.062	1.829	0.151	1.809	0.003
A038	0.820	0.724	0.757	0.940	0.936	0.631	0.953	0.892
A039	2.145	0.000	1.559	0.012	1.372	0.053	1.343	0.017
A040	1.104	0.996	1.073	0.997	1.038	0.999	1.035	1.000
A041	1.349	0.779	1.584	0.357	1.851	0.276	3.610	0.026
A042	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A043	1.068	0.919	1.036	0.932	1.011	0.995	0.969	0.877
A044	1.161	0.750	1.244	0.223	1.863	0.357	3.430	0.001
A045	1.745	0.000	1.476	0.000	1.474	0.000	1.521	0.016
A046	0.249	0.000	0.358	0.000	0.498	0.001	0.588	0.000
A047	0.923	0.438	0.877	0.663	0.823	0.224	0.786	0.403
A048	0.657	0.903	0.577	0.919	1.317	0.938	4.049	0.861
A049	1.042	0.653	1.099	0.680	1.109	0.967	1.273	0.622
A050	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A051	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A052	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A053	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A054	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A055	1.064	0.983	1.036	0.990	1.017	0.710	1.008	0.615

Table A3. Cont.

Series' Code	Forecasting Horizon							
	h = 1		h = 3		h = 6		h = 12	
	RRMSE	KSPA <i>p</i> -Value	RRMSE	KSPA <i>p</i> -Value	RRMSE	KSPA <i>p</i> -Value	RRMSE	KSPA <i>p</i> -Value
A056	1.346	0.536	1.166	0.728	1.116	0.897	1.089	0.928
A057	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A058	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A059	1.059	0.874	1.044	1.000	1.056	0.990	1.044	0.996
A060	1.460	0.124	1.439	0.133	1.353	0.374	1.317	0.174
A061	5.321	0.000	3.518	0.012	2.806	0.004	1.565	0.000
A062	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A063	1.061	0.528	0.816	0.562	0.765	0.610	0.892	0.100
A064	0.815	0.690	0.788	1.000	0.850	0.579	0.423	0.834
A065	0.931	0.926	0.888	0.994	0.887	0.996	0.892	0.739
A066	2.509	0.008	2.219	0.039	1.736	0.229	1.189	0.739
A067	1.085	0.750	0.876	0.610	0.733	0.249	0.490	0.036
A068	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A069	1.063	0.975	1.038	0.999	1.037	0.644	1.028	0.704
A070	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A071	0.874	0.653	0.858	0.680	0.845	0.396	0.883	0.999
A072	0.910	0.979	0.869	0.723	0.903	0.766	0.946	0.952
A073	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A074	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A075	1.389	0.135	1.523	0.389	1.463	0.791	1.352	0.693
A076	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A077	1.089	0.915	1.084	0.997	1.172	0.808	1.373	0.707
A078	1.105	0.996	1.084	0.997	1.095	0.958	1.083	0.707
A079	0.970	0.915	1.018	0.754	1.105	0.958	1.235	0.707
A080	1.081	0.999	1.055	0.979	1.032	1.000	1.032	1.000
A081	1.084	0.987	1.068	0.990	1.092	0.938	1.086	0.861
A082	0.977	0.998	1.040	0.844	1.059	0.744	1.049	0.991
A083	0.781	0.383	0.847	0.562	0.900	0.977	0.592	0.665
A084	0.634	0.004	0.544	0.033	0.396	0.041	0.054	0.002
A085	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A086	2.643	0.000	2.357	0.013	2.123	0.214	1.715	0.182
A087	2.030	0.023	1.758	0.147	1.552	0.162	1.293	0.268
A088	0.907	0.996	0.982	0.791	1.031	0.915	1.129	0.268
A089	1.868	0.198	1.255	0.791	1.006	0.546	0.924	0.194
A090	1.132	0.968	1.099	0.997	1.120	0.810	1.118	0.594
A091	0.507	0.513	0.132	0.131	0.009	0.098	0.000	0.084
A092	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A093	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
A094	3.369	0.000	2.508	0.019	2.094	0.098	1.827	0.020
A095	3.167	0.000	2.090	0.004	1.724	0.016	1.541	0.004
A096	1.692	0.020	1.696	0.086	1.798	0.024	1.867	0.006
A097	1.188	0.591	1.077	0.957	1.039	0.723	1.049	0.287
A098	0.587	0.059	0.649	0.015	0.765	0.352	0.902	0.563
A099	0.780	0.261	0.838	0.877	0.897	0.598	0.953	0.987
A100	0.947	0.612	0.736	0.086	0.729	0.278	0.720	0.078

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