Supplementary material

1. Necessary concepts

1.1 The conventional GM(1,1) model

For a given system, we can obtain the original time sequence that is $X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right)$, where $x^{(0)}(i) > 0, i = 1,2,\cdots,n$ is equally-spaced over time and n is more than four in number. Subsequently, the detailed steps of GM(1,1) are outlined below:

Step 1: Conducting the first-order accumulated generated operation ($1\text{-}AGO$) for the collected $X^{(0)}$, the new generalized accumulation sequence is presented:

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right) \tag{1}$$

where $x^{(0)}(1) = x^{(1)}(1)$ and the kth entry is defined as $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1,2,\cdots,n$.

Step 2: Establishing GM(1,1) for the new time series. The form of the first-order grey differential equation of GM(1,1) is given by

$$x^{(0)}(k) + az^{(1)}(k) = b, \tag{2}$$

where $z^{(1)}(k)$ is called the background value, for which the kth entry is defined as $z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1), k = 2,3,\cdots,n$. Then, the corresponding albinism differential equation of GM(1,1) is:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b. \tag{3}$$

where a means the development coefficient and b represents the grey action item.

Step 3: Calculating the parameters a and b. Substituting the values of k into Eq. (2), one can obtain

$$\begin{aligned} x^{(0)}(2) + az^{(1)}(2) &= b \\ x^{(0)}(3) + az^{(1)}(3) &= b \\ &\vdots \\ x^{(0)}(n) + az^{(1)}(n) &= b \end{aligned}. \tag{4}$$

In matrix form, $\mathbf{B} = \mathbf{A}\widehat{\boldsymbol{\theta}}$, where

$$\mathbf{A} = \begin{bmatrix} -z^{(0)}(2) & 1 \\ -z^{(0)}(3) & 1 \\ \vdots & \vdots \\ -z^{(0)}(n) & 1 \end{bmatrix}, \mathbf{B} = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \widehat{\boldsymbol{\theta}} = \begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix}. \tag{5}$$

By solving the above matrix form in Eq. (4), the least-squares estimation for a and b are $\widehat{\boldsymbol{\theta}} = [\hat{a}, \hat{b}]^T = (\mathbf{A}^{\mathbf{T}}\mathbf{A})^{-1}\mathbf{A}^{\mathbf{T}}\mathbf{B}$.

Step 4: Obtaining the newly-generated sequence for forecasting, based on the initial condition of $\hat{x}^{(1)}(1) = x^{(0)}(1) = x^{(1)}(1)$, which is given by

$$\hat{x}^{(1)}(k) = \left[x^{(1)}(1) - \hat{b}/\hat{a}\right]e^{-\hat{a}(k-1)} + \hat{b}/\hat{a}, k = 2,3,\cdots,n,n+1,\cdots \tag{6}$$

Step 5: Calculating the fitted and forecasted values in the original domain by using the inverse $1\text{-}AGO$ with the expression $\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1)$, which can be expressed by

$$\hat{x}^{(0)}(k) = \left[x^{(1)}(1) - \hat{b}/\hat{a}\right]\left(1 - e^{\hat{a}}\right)e^{-\hat{a}(k-1)}, k = 2,3,\cdots,n,n+1,\cdots, \tag{7}$$

where $\hat{x}^{(0)}(k)(k = 1,2,\cdots,n)$ are fitted values and $\hat{x}^{(0)}(k)(k \geq n+1)$ are forecasted values.

2.2 The seasonal GM(1,1) model

As Eq. (7) reveals, the prediction equation in the conventional GM(1,1) model is essentially a function for describing the exponential time series. If a given sequence has seasonal fluctuations, this model will perform unsatisfactory results due to its exponential mechanism. To address such issues, Wang et al. (2018c) put forward a seasonal grey model (SGM(1,1)) based on the accumulation operators that are generated by using seasonal factors. The detailed process of this model can be introduced as follows.

Suppose that $X^{(0)}$ represents the seasonally-influenced original data, which is defined in Section 2.1 and S stands for a first-order seasonal accumulated generated operation ($1\text{-}SAGO$), then one can obtain

$$X_s^{(1)} = X^{(0)}S = \left(x^{(1)}(1)s, x^{(1)}(2)s, \cdots, x^{(1)}(n)s\right) \tag{8}$$

where

$$x^{(1)}(k)s = \sum_{j=1}^{k} x^{(0)}(j)/f_s(j), k = 1,2,\cdots,n \tag{9}$$

for which $f_s(j)$ is the seasonal factor acting at the $j\,th$ data point in the collected data sequence. It represents a dimensionless parameter that can reflect the average seasonally-affected degree, for which the actual value in different data point deviates from the system trend due to the seasonal fluctuations. Then, its precise expression can be obtained by

$$f_s(j) = \frac{\bar{x}_M^{(0)}(j)}{\bar{x}_{MN}^{(0)}(j)} \tag{10}$$

where M stands for the number of seasonal cycles and N is the year of the $j\,th$ data point. For instance, $M = 4$ means the quarterly time series, while $M = 12$ represents the monthly seasonal cycles. Besides, $\bar{x}_M^{(0)}(j)$ and $\bar{x}_{MN}^{(0)}(j)$ represent the average value for the quarter or month at the $j\,th$ data point and the total average value for all quarters or months, respectively.

Subsequently, based on the processed time series by using the $1\text{-}SAGO$, we can have the functions of SGM(1,1) as follows.

The form of the grey differential equation of SGM(1,1) is given by

$$x^{(0)}(k)/f_s(k) + a_s z_s^{(1)}(k) = b_s \tag{11}$$

where $z_s^{(1)}(k) = 0.5x_s^{(1)}(k) + 0.5x_s^{(1)}(k-1), k = 2,3,\cdots,n$. Then, the corresponding albinism differential equation of SGM(1,1) is:

$$\frac{dx_s^{(1)}(t)}{dt} + a_s x_s^{(1)}(t) = b_s. \tag{12}$$

where a_s means the development coefficient and b_s represents the grey action item. The parameter $\hat{\boldsymbol{\eta}} = [\hat{a}_s, \hat{b}_s]^T$ can be estimated by using the least square method: $\hat{\boldsymbol{\eta}} = [\hat{a}_s, \hat{b}_s]^T = (\mathbf{C}^\mathbf{T}\mathbf{C})^{-1}\mathbf{C}^\mathbf{T}\mathbf{D}$, where

$$\mathbf{C} = \begin{bmatrix} -z_s^{(0)}(2) & 1 \\ -z_s^{(0)}(3) & 1 \\ \vdots & \vdots \\ -z_s^{(0)}(n) & 1 \end{bmatrix}, \mathbf{D} = \begin{bmatrix} x^{(0)}(2)/f_s(2) \\ x^{(0)}(3)/f_s(3) \\ \vdots \\ x^{(0)}(n)/f_s(4) \end{bmatrix}, \hat{\boldsymbol{\theta}} = \begin{bmatrix} \hat{a}_s \\ \hat{b}_s \end{bmatrix}. \tag{13}$$

Based on the estimated parameters, the formation of SGM(1,1) is

$$\hat{x}_s^{(1)}(k) = \left[x^{(1)}(1)/f_s(1) - \hat{b}_s/\hat{a}_s\right]e^{-\hat{a}_s(k-1)} + \hat{b}_s/\hat{a}_s, k = 2,3,\cdots,n,n+1,\cdots \tag{14}$$

The final fitted and forecasted value in the original domain can be obtained by

$$\hat{x}^{(0)}(k) = f_s(k)\left[\hat{x}_s^{(1)}(k) - \hat{x}_s^{(1)}(k-1)\right], k = 2,3,\cdots,n,n+1,\cdots \tag{15}$$

Though the GM(1,1) and its variants have certain advantages, such as simple structure and high precision, even facing a limited amount of data, it has certain disadvantages that are not suitable for middle- and long-term forecasting due to the inherent errors generated by the transformation from the discrete function to the continuous one (Ding, 2019; Xie and Liu, 2009). To be specific, these transformation errors might significantly reduce the accuracy of estimating the grey coefficient a, thereby generating unsatisfactory forecasting results. Table S1 demonstrates the relationships between the development and applicability of GM(1,1). Therefore, to deal with such issues, the discrete grey model (SGM(1,1))model is proposed by Xie and Liu (Xie and Liu, 2009), which can strikingly improve the forecasting performance in modeling various time sequences.

Table S1 Relationships between the development coefficient and applicability of GM(1,1) (Liu and Deng, 2000)

Range of a	Applicability
$-0.3 \le a$	Suitable for middle- and long-term forecasting

$-0.5 \le a < -0.3$	Suitable for short-term forecasting and harmful for middle- and long-term forecasting
$-0.8 \le a < -0.5$	Suitable for short-term forecasting, but negative results
$-1.0 \le a < -0.8$	Applications with corrected results by the residual errors
$-1.0 > a$	Not applicable in any situation

3.3 The DGM(1,1) model

In order to eliminate the transformation errors inherently stacked in the conventional GM(1,1) model, Xie and Liu (2009) proposed the discrete grey model, whose detailed procedures are outlined as follows.

Step 1: Collecting the raw observations $X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right)$ and conducting the first-order accumulated generated operation ($1\text{-}AGO$), the new generalized accumulation sequence is presented:

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right) \tag{16}$$

where $x^{(0)}(1) = x^{(1)}(1)$ and the kth entry is defined as $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1,2,\cdots,n$.

Step 2: Establishing DGM(1,1) for the new time series, whose form can be given by

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2 \tag{17}$$

where β_1 means the development coefficient and β_2 represents the grey constant.

Step 3: Calculating the parameters β_1 and β_2. Substituting the values of k in to Eq. (17), one can obtain

$$\begin{aligned} x^{(1)}(2) &= \hat{\beta}_1 x^{(1)}(1) + \hat{\beta}_2 \\ x^{(1)}(3) &= \hat{\beta}_1 x^{(1)}(2) + \hat{\beta}_2 \\ &\vdots \\ x^{(1)}(n) &= \hat{\beta}_1 x^{(1)}(n-1) + \hat{\beta}_2 \end{aligned} \tag{18}$$

In matrix form, $\mathbf{H} = \mathbf{G}\widehat{\boldsymbol{\beta}}$, where

$$\mathbf{G} = \begin{bmatrix} -x^{(1)}(1) & 1 \\ -x^{(1)}(2) & 1 \\ \vdots & \vdots \\ -x^{(1)}(n-1) & 1 \end{bmatrix}, \mathbf{H} = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix}, \widehat{\boldsymbol{\beta}} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix}. \tag{19}$$

By solving the above matrix form in Eq. (18), the least-squares estimation for β_1 and β_2 are $\widehat{\boldsymbol{\beta}} = \left[\hat{\beta}_1, \hat{\beta}_2\right]^T = (\mathbf{G}^{\mathbf{T}}\mathbf{G})^{-1}\mathbf{G}^{\mathbf{T}}\mathbf{H}$.

Step 4: Obtaining the newly-generated sequence for forecasting based on the initial condition of $\hat{x}^{(1)}(1) = x^{(0)}(1) = x^{(1)}(1)$, which is given by

$$\hat{x}^{(1)}(k+1) = \hat{\beta}_1^k x^{(1)}(1) + \frac{1-\hat{\beta}_1^k}{1-\hat{\beta}_1} * \hat{\beta}_2, k = 1,2,\cdots,n,n+1,\cdots \quad (20)$$

Step 5: Calculating the fitted and forecasted values in the original domain by using the inverse $1\text{-}AGO$ with the expression $\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1)$, which can be expressed by

$$\hat{x}^{(0)}(k+1) = (\hat{\beta}_1 - 1) * \left[x^{(1)} - \frac{\hat{\beta}_2}{1-\hat{\beta}_1}\right] * \hat{\beta}_1^k, k = 1,2,\cdots,n,n+1,\cdots, \quad (21)$$

where $\hat{x}^{(0)}(k)(k = 1,2,\cdots,n)$ are fitted values and $\hat{x}^{(0)}(k)(k \geq n+1)$ are forecasted values.

Although the DGM(1,1) model can eliminate the inherent jumping errors of the conventional GM(1,1) model, it still limited capability to describe seasonal time series that are widely existed in the real world. Thus, to accurately estimate the seasonal fluctuations, a novel seasonal discrete grey model is put forward in this work for predicting electricity consumption and production in China.

2. The forecasted error of the competing models when m=33

Table S2 Error analysis of the competing models when m=33

	Electricity consumption forecasting				Electricity production forecasting			
Model	*MAE*	*MARE*	*MSE*	*MSRE*	*MAE*	*MARE*	*MSE*	*MSRE*
SDGM(1,1)	**398.1235**	**0.0861**	**256095.3200**	**0.0105**	**124.2342**	**0.0422**	**39878.4960**	**0.0031**
SGM(1,1)	390.4013	0.0847	244982.4286	0.0104	167.3441	0.0635	56546.7458	0.0066
SARIMA	468.7037	0.0966	391690.4211	0.0144	150.2226	0.0588	55456.3081	0.0068
LSSVR	581.8624	0.1255	592609.4834	0.0223	337.0271	0.1022	459368.2021	0.0225
LSTM	739.9751	0.1762	784881.0025	0.0464	388.1003	0.1499	310346.1707	0.0340
MLP	865.0773	0.1894	1344691.2820	0.0516	546.8208	0.2019	711490.7436	0.0590
HW	489.2145	0.1067	449044.6649	0.0208	218.0218	0.0694	144734.4185	0.0094
Snavie	656.8130	0.1484	577455.9010	0.0272	386.5183	0.1477	244927.5598	0.0285

Note: the best performance values are given in bold.

As Table S2 shows, a similar conclusion can be found with the results (m=11) that the proposed model still generates the best forecasting performance when m=33. Therefore, the empirical cases demonstrate that the newly-designed model is reliable and practical to predict electricity consumption and production.

3. The results of the *MCS* test when m=33

Table S3 The results of the *MCS* test when m=33

		T_R				T_{SQ}			
		MAE	*MARE*	*MSE*	*MSRE*	*MAE*	*MARE*	*MSE*	*MSRE*
Electricity consumption forecasting	SDGM(1,1)	0.549	0.697	0.357	0.851	0.549	0.697	0.357	0.851
	SGM(1,1)	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
	SARIMA	0.074	0.099	0.02	0.011	0.051	0.149	0.01	0.019
	LSSVR	0	0	0.006	4.00E-04	6.00E-04	7.00E-04	0.006	7.00E-04
	LSTM	0	0	0	0	0	0	0	0
	MLP	0	0	2.00E-04	0	0	0	2.00E-04	0
	HW	0.074	0.055	0.027	0.004	0.101	0.074	0.034	0.003
	Snaive	0	0	2.00E-04	0	0	0	3.00E-04	0
Electricity production forecasting	SDGM(1,1)	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
	SGM(1,1)	0.006	0	0.179	3.00E-04	9.00E-04	0	0.076	0
	SARIMA	0.058	2.00E-04	0.179	3.00E-04	0.058	2.00E-04	0.149	1.00E-04
	LSSVR	4.00E-04	0	0.014	3.00E-04	1.00E-04	0	0.003	0
	LSTM	0	0	0	0	0	0	0	0
	MLP	0	0	0	0	0	0	0	0
	HW	0.003	0	0.014	3.00E-04	1.00E-04	0	0.003	0
	Snaive	0	0	0	0	0	0	0	0

4. The results of the DM test when m=33

Table S4 The results of the *DM* test when m=33

			SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive
Electricity consumption forecasting	*MAE*	*DW*	1.007	-3.104	-3.588	-7.291	-4.031	-2.726	-7.798
		p	0.316	0.002	5E-04	3E-11	9E-05	0.007	2E-12
	MARE	*DW*	0.2	-3.001	-4.871	-6.543	-7.595	-4.24	-7.907
		p	0.842	0.003	3E-06	1E-09	5E-12	4E-05	1E-12
	MSE	*DW*	1.346	-2.191	-1.62	-3.65	-2.049	-1.904	-2.64
		p	0.18	0.03	0.108	4E-04	0.042	0.059	0.009
	MSRE	*DW*	-0.719	-2.237	-2.512	-3.211	-3.986	-3.634	-5.249
		p	0.473	0.027	0.013	0.002	1E-04	4E-04	6E-07
Electricity production forecasting	*MAE*	*DW*	-2.962	-1.698	-3.385	-6.65	-4.121	-4.337	-10.08
		p	0.003	0.091	8E-04	1E-10	5E-05	2E-05	1E-20
	MARE	*DW*	-6.934	-6.042	-5.022	-11.33	-13.61	-7.084	-13.92
		p	3E-11	5E-09	9E-07	8E-25	8E-33	1E-11	6E-34

MSE	*DW*	-0.443	-0.265	-2.224	-2.913	-1.52	-2.588	-4.686
	p	0.658	0.791	0.027	0.004	0.13	0.01	4E-06
MSRE	*DW*	-4.012	-5.279	-2.375	-5.883	-7.315	-5.535	-8.436
	p	8E-05	3E-07	0.018	1E-08	3E-12	7E-08	2E-15

5. The results of the SPA test when m=11 and m=33

Table S5 The results of the *SPA* test when m=11

		Electricity consumption forecasting							Electricity production forecasting						
		SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive
SDGM(1,1)	*MAE*	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	MARE	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	MSE	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	MSRE	1	1	1	1	1	1	1	1	1	1	1	1	1	1
		SDGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive	SDGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive
SGM(1,1)	*MAE*	0.425	1	1	1	1	1	1	0.062	1	1	1	1	1	1
	MARE	0.314	1	1	1	1	1	1	0.004	1	1	1	1	1	1
	MSE	0.317	1	1	1	1	1	1	0.444	1	1	1	1	1	1
	MSRE	0.114	1	1	1	1	1	1	0.011	1	1	1	1	1	1
		SDGM(1,1)	SGM(1,1)	LSSVR	LSTM	MLP	HW	Snaive	SDGM(1,1)	SGM(1,1)	LSSVR	LSTM	MLP	HW	Snaive
SARIMA	*MAE*	0.099	0.119	1	1	1	1	1	0.083	0.161	1	1	1	0.286	1
	MARE	0.089	0.112	1	1	1	1	1	0.087	0.297	1	1	1	1	1
	MSE	0.078	0.081	1	1	1	0.132	0.379	0.056	0.061	1	1	1	0.052	1
	MSRE	0.059	0.08	1	1	1	0.158	0.165	0.059	0.086	1	1	1	0.158	1
		SDGM(1,1)	SGM(1,1)	SARIMA	LSTM	MLP	HW	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSTM	MLP	HW	Snaive
LSSVR	*MAE*	0.002	0.003	0.015	1	1	0.018	0.093	5E-04	0.002	0.011	1	1	0.009	1
	MARE	7E-04	9E-04	0.027	1	1	0.035	0.098	2E-04	0.002	0.001	1	1	0.004	1
	MSE	0.017	0.015	0.048	0.13	1	0.033	0.041	0.01	0.012	0.127	1	1	0.051	0.369
	MSRE	0.008	0.01	0.155	0.191	1	0.069	0.03	0.014	0.02	0.268	1	1	0.122	1
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	MLP	HW	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	MLP	HW	Snaive
LSTM	*MAE*	0	0	4E-04	0.513	1	8E-04	9E-04	0	0	0	0	1	0	0.098
	MARE	0	0	0.008	0.412	1	0.008	0.005	0	0	0	0	1	0	1
	MSE	1E-04	1E-04	0.036	1	1	0.006	0.001	0	0	0.007	0.026	1	0.001	0.009
	MSRE	0	0	0.386	1	1	0.122	0.002	0	0	0.003	0.001	1	6E-04	0.195
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	HW	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	HW	Snaive
MLP	*MAE*	0	0	1E-04	0.058	0.039	1E-04	0.001	0	0	0	0	0	0	0
	MARE	0	0	2E-04	0.041	0.024	3E-04	3E-04	0	0	0	0	0	0	0
	MSE	0.014	0.014	0.029	0.221	0.07	0.023	0.026	0.002	0.003	0.005	0.009	0.012	0.005	0.007
	MSRE	0	0	0.032	0.204	0.016	0.006	6E-04	0	0	0	0	0	0	0
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	Snaive
HW	*MAE*	0.054	0.066	0.383	1	1	1	1	0.106	0.21	1	1	1	1	1
	MARE	0.043	0.058	0.313	1	1	1	1	0.075	0.279	0.466	1	1	1	1
	MSE	0.07	0.082	1	1	1	1	1	0.113	0.119	1	1	1	1	1
	MSRE	0.046	0.06	1	1	1	1	0.229	0.072	0.105	1	1	1	1	1
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW
Snaive	*MAE*	0	0	0.039	1	1	1	0.028	0	0	0	1E-04	1	1	0
	MARE	0	0	0.145	1	1	1	0.167	0	0	0	0	0.29	1	0
	MSE	2E-04	4E-04	1	1	1	1	0.289	0	0	0.143	1	1	1	0.012
	MSRE	0.008	0.022	1	1	1	1	1	0	0	0.007	0.009	1	1	0

Table S6 The results of the *SPA* test when m=33

		Electricity consumption forecasting							Electricity production forecasting						
		SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive
SDGM(1,1)	*MAE*	0.273	1	1	1	1	1	1	1	1	1	1	1	1	1
	MARE	0.356	1	1	1	1	1	1	1	1	1	1	1	1	1
	MSE	0.164	1	1	1	1	1	1	1	1	1	1	1	1	1
	MSRE	0.414	1	1	1	1	1	1	1	1	1	1	1	1	1
		SDGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive	SDGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	Snaive
SGM(1,1)	*MAE*	1	1	1	1	1	1	1	2E-04	0.044	1	1	1	1	1
	MARE	1	1	1	1	1	1	1	0	0.05	1	1	1	1	1
	MSE	1	1	1	1	1	1	1	0.021	0.45	1	1	1	1	1
	MSRE	1	1	1	1	1	1	1	0	1	1	1	1	1	1
		SDGM(1,1)	SGM(1,1)	LSSVR	LSTM	MLP	HW	Snaive	SDGM(1,1)	SGM(1,1)	LSSVR	LSTM	MLP	HW	Snaive
SARIMA	*MAE*	0.023	0.022	1	1	1	1	1	0.056	1	1	1	1	1	1
	MARE	0.06	0.082	1	1	1	1	1	0.001	1	1	1	1	1	1
	MSE	0.006	0.005	1	1	1	1	1	0.103	1	1	1	1	1	1
	MSRE	0.008	0.023	1	1	1	1	1	1E-04	0.315	1	1	1	1	1
		SDGM(1,1)	SGM(1,1)	SARIMA	LSTM	MLP	HW	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSTM	MLP	HW	Snaive
LSSVR	*MAE*	0	0	0.041	1	1	0.139	1	6E-04	0.002	0.003	1	1	0.031	1
	MARE	0	0	0.02	1	1	0.16	1	0	1E-04	3E-04	1	1	0.005	1
	MSE	0.002	0.003	0.075	1	1	0.199	0.374	0.027	0.032	0.034	0.195	1	0.07	0.13
	MSRE	2E-04	1E-04	0.029	1	1	0.41	1	0.006	0.014	0.013	1	1	0.034	1
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	MLP	HW	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	MLP	HW	Snaive
LSTM	*MAE*	0	0	2E-04	1E-04	1	8E-04	0.018	0	0	0	0.123	1	0	0.474
	MARE	0	0	0	1E-04	1	1E-04	0.009	0	0	0	1E-04	1	0	0.353
	MSE	0	0	0.004	0.022	1	0.016	0.008	0	0	0	1	1	3E-04	0.036
	MSRE	1E-04	0	3E-04	0.002	1	0.002	0.007	0	0	0	0.024	1	0	0.009
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	HW	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	HW	Snaive
MLP	*MAE*	0	0	0	2E-04	0.044	0	0.002	0	0	0	1E-04	1E-04	0	2E-04
	MARE	0	0	0	0	0.155	0	1E-04	0	0	0	0	0	0	0
	MSE	5E-04	5E-04	0.002	0.005	0.027	7E-04	0.006	0.002	0.002	0.003	0.14	0.022	0.006	0.011
	MSRE	0	0	0	0	0.212	0	2E-04	0	0	0	0	0	0	0
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	Snaive	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	Snaive
HW	*MAE*	0.059	0.061	0.327	1	1	1	1	0.001	0.044	0.007	1	1	1	1
	MARE	0.038	0.063	0.14	1	1	1	1	1E-04	0.16	0.023	1	1	1	1
	MSE	0.031	0.035	0.25	1	1	1	1	0.007	0.016	0.012	1	1	1	1
	MSRE	0.005	0.008	0.031	1	1	1	1	0	0.033	0.034	1	1	1	1
		SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW	SDGM(1,1)	SGM(1,1)	SARIMA	LSSVR	LSTM	MLP	HW
Snaive	*MAE*	0	0	0.001	8E-04	1	1	0.013	0	0	0	0.159	1	1	0
	MARE	0	0	0	0	1	1	0.006	0	0	0	0	1	1	0
	MSE	0	0	0.031	1	1	1	0.173	0	0	0	1	1	1	0.009
	MSRE	0	0	0.001	0.011	1	1	0.137	0	0	0	0.173	1	1	0