

Evaluating the benefit of grid-based weather information in energy forecasting

Marcel Herm

INSTITUT FÜR AUTOMATION UND ANGEWANDTE INFORMATIK



Overview

1 Introduction

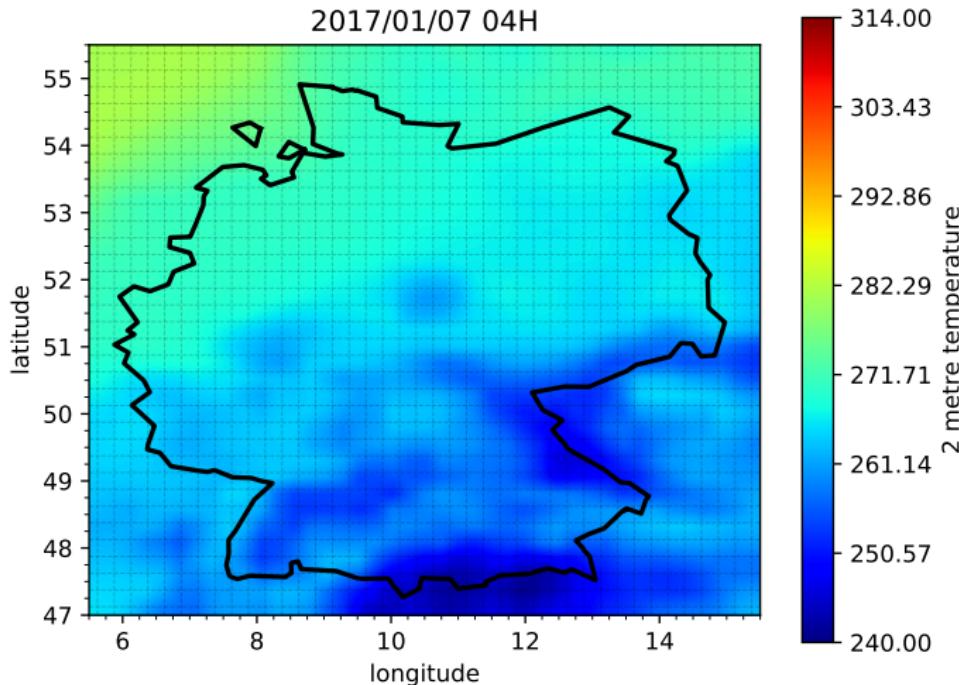
2 Related Work

3 Methods

4 Evaluation

5 Conclusion

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Related Works

paper	type of weather data	forecast time series	methods	forecast horizon
Ludwig u. a. (2015)	station-based	energy prices	ARMA,ARMAX, LASSO,RF	24h
Salcedo-Sanz u. a. (2018)	grid-based	solar radiation	ELM,CRO,MARS, MLR,SVR,GGA	24h
Diagne u. a. (2013)	grid-based	solar radiation	ARMA,ARIMA, CARDS,NN,WNN	5 min-6h
Aguiar u. a. (2016)	mixed	solar radiation	NN	1-6h
Bofinger und Heilscher (2006)	mixed	solar power	MOS, IDW	24-120h
Haben u. a. (2018)	station-based	low voltage electricity load	KDE,SSLR,ARWD, ARWDY,HWT	up to 4 days
Alessandrini u. a. (2015)	station-based	wind power	ANEN	0-132h
Sperati u. a. (2016)	grid-based	solar power	PDF,NN,VD, EMOS,PE	0-72h
De Felice u. a. (2015)	grid-based	electricity demand	LR,SVM	1-2 months
Davò u. a. (2016)	grid-based	wind power, solar radiation	PCA,ANEN,NN	0-72h
This thesis	grid-based	electricity load	ARMA,ARMAX	1h

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ARMA

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \rho_j \epsilon_{t-j} + \epsilon_t \quad (1)$$

ARMAX

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \rho_j \epsilon_{t-j} + \sum_{k=1}^n \eta_k x_k + \epsilon_t \quad (2)$$

Mean Absolute Percentage Error

$$MAPE = \frac{1}{k} \times 100 \sum_{i=1}^k \left| \frac{y_i - \hat{y}_i}{y_i} \right| . \quad (3)$$

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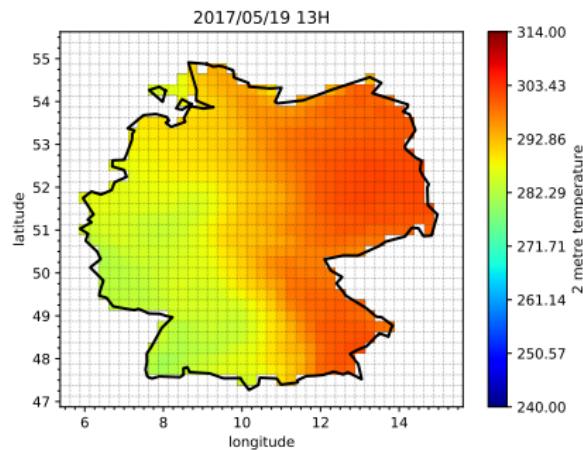
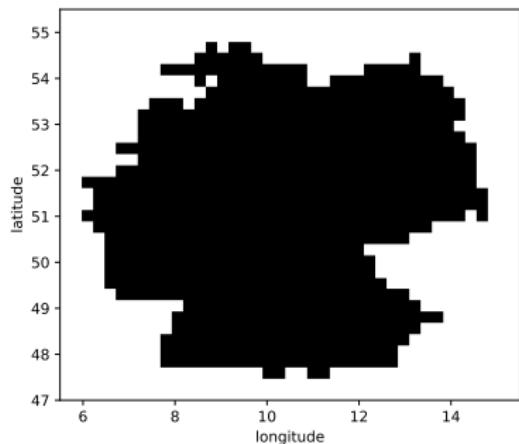
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Evaluation I

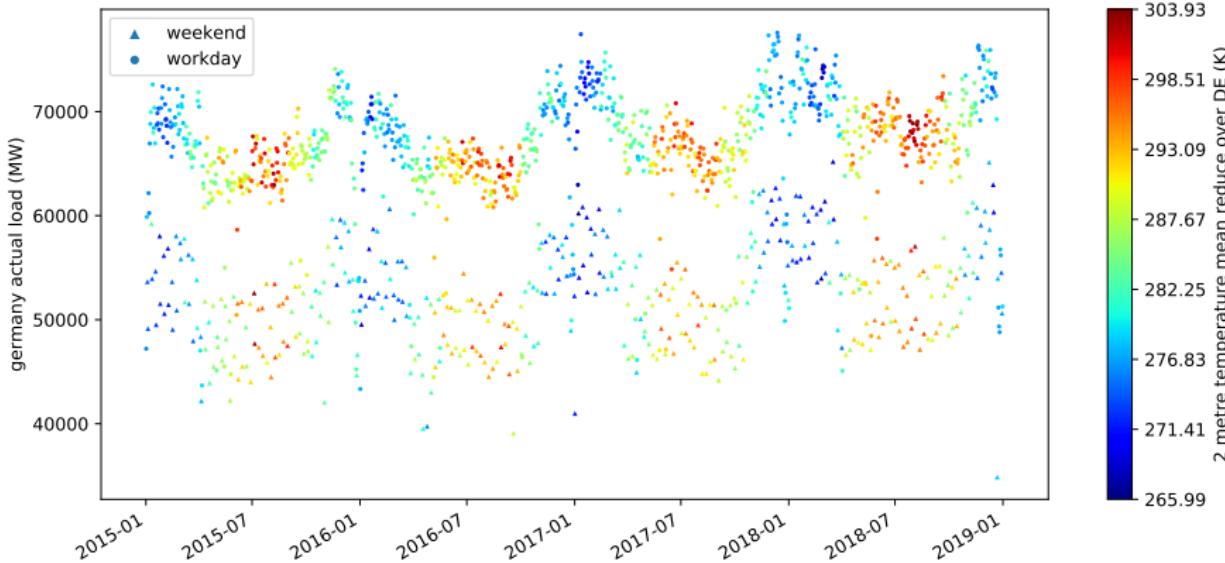
Data filtered using shapefile from Eurostat¹.



¹<https://ec.europa.eu/eurostat/de/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts>

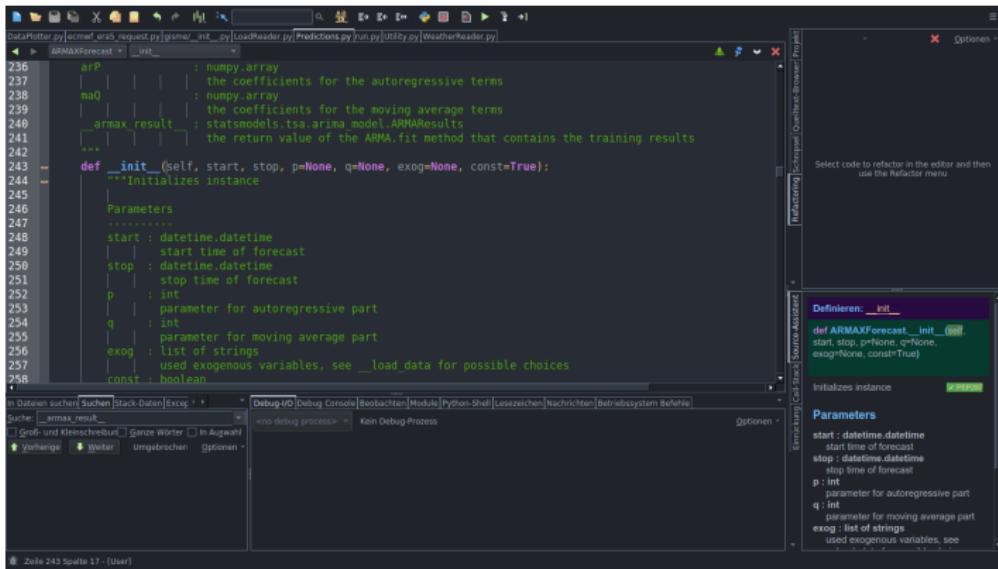
Evaluation II

Stuffy stuff.



Evaluation III

Wing stuffy². optional, max 30s



The screenshot shows the Wing IDE interface with the following details:

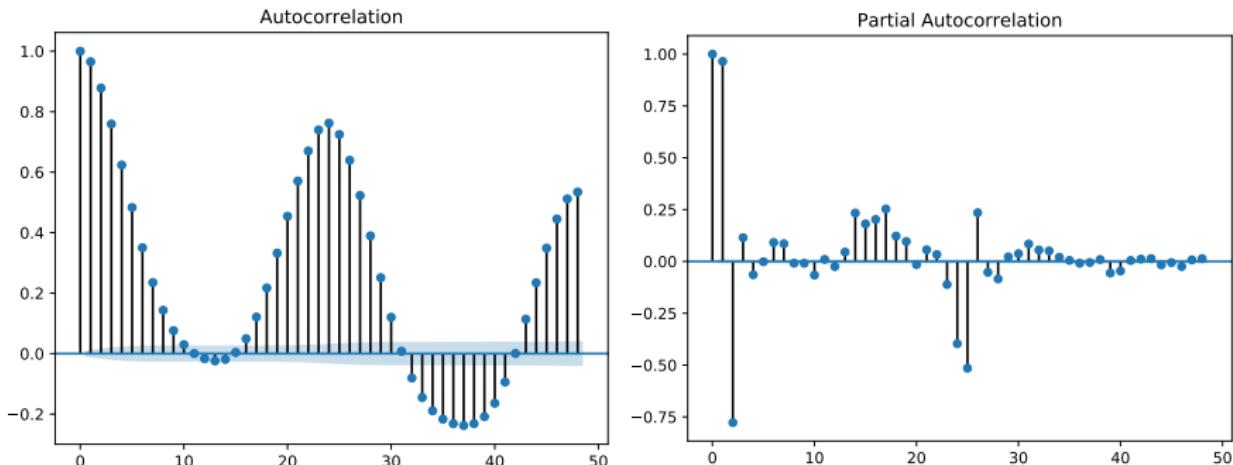
- Editor Area:** Displays the `ARMAXForecast.py` file. The code defines a class `ARMAXForecast` with an `__init__` method. The docstring for `__init__` is:

```
def __init__(self, start, stop, p=None, q=None, exog=None, const=True):  
    """Initializes instance  
  
    Parameters  
    -----  
    start : datetime.datetime  
        start time of forecast  
    stop : datetime.datetime  
        stop time of forecast  
    p : int  
        parameter for autoregressive part  
    q : int  
        parameter for moving average part  
    exog : list of strings  
        used exogenous variables, see __load_data for possible choices  
    const : boolean
```
- Refactoring Sidebar:** Shows a tooltip for the `__init__` method with the text "Initializes instance". It also lists parameters: `start`, `stop`, `p`, `q`, `exog`, and `const`.
- Bottom Status Bar:** Shows the current line and column: "Zeile 243 Spalte 17 - [User]".

²<https://wingware.com/>

Evaluation IV

Autocorrelation and partial autocorrelation function.



Evaluation V

MA(q) 0

1

2

3

4

5

>

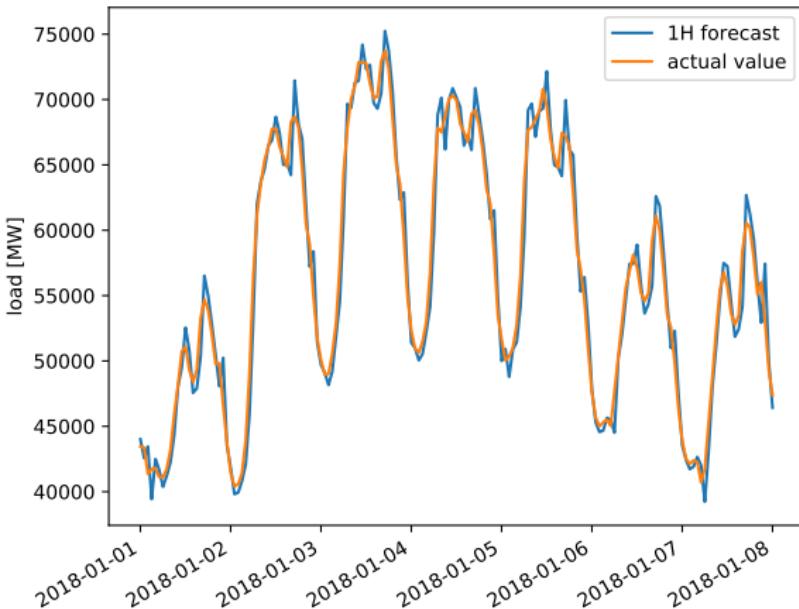
AR(p)

v

AIC	1	489489.23	472851.05	467543.07	466091.08	465622.11	464728.34
BIC		489513.76	472883.76	467583.96	466140.14	465679.35	464793.76
HQIC		489497.15	472861.61	467556.27	466106.92	465640.59	464749.47
AIC	2	464699.50	464253.96	464204.94	464190.14	464054.46	463634.12
BIC		464732.21	464294.85	464254.01	464247.39	464119.87	463707.72
HQIC		464710.06	464267.16	464220.79	464208.63	464075.58	463657.89
AIC	3	464324.69	464226.02	464202.92	463643.15	462483.99	462271.48
BIC		464365.58	464275.09	464260.16	463708.57	462557.59	462353.25
HQIC		464337.89	464241.87	464221.4	463664.27	462507.75	462297.88
AIC	4	464171.28	464173.25	462433.17	462985.37	462149.01	-
BIC		464220.35	464230.49	462498.59	463058.97	462230.78	
HQIC		464187.13	464191.73	462454.29	463009.14	462175.41	
AIC	5	464173.18	463588.38	462944.78	-	462138.70	-
BIC		464230.42	463653.80	463018.38		462228.65	
HQIC		464191.66	463609.50	462968.54		462167.74	

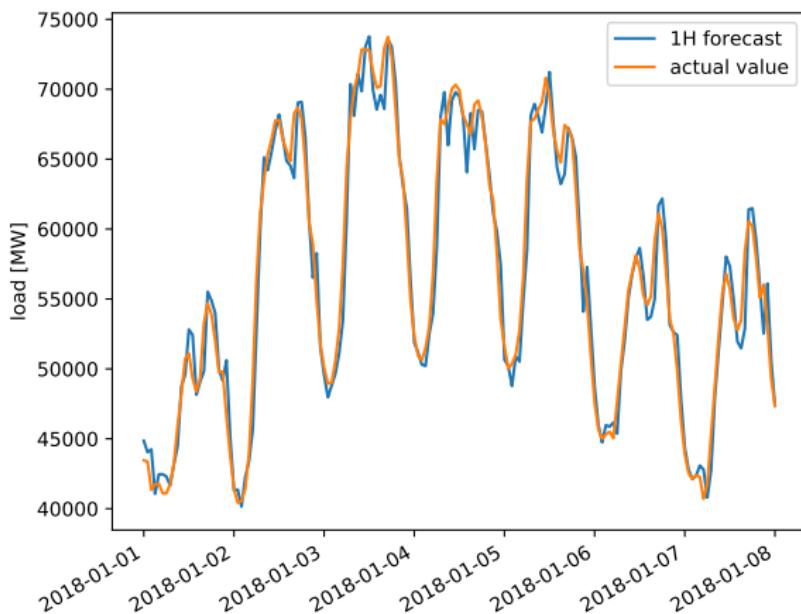
Evaluation VI

Only load ARMA(2,2) from 2017/12/31 to 2018/01/08 using load data from 2015/01/080 to 2017/12/31 for training.



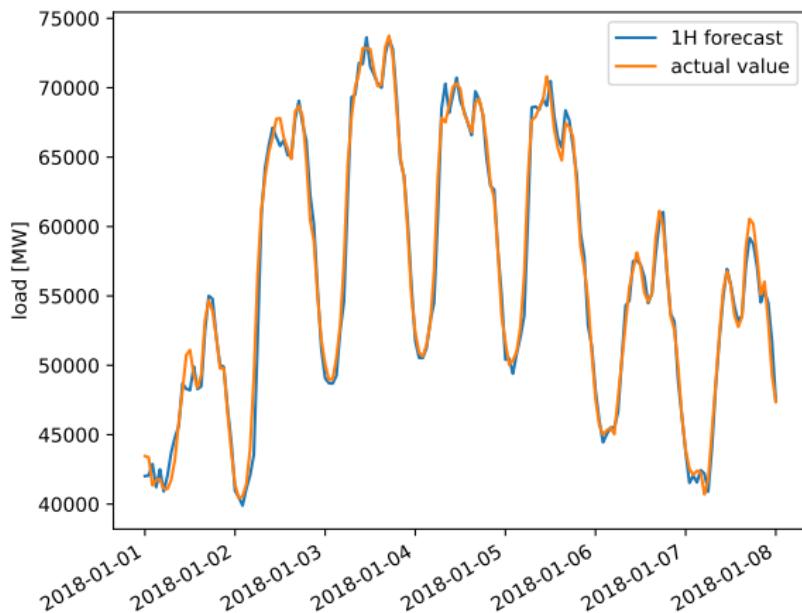
Evaluation VII

Forecast from 2017/12/31 to 2018/01/08 for ARMAX(2,2) with load data from 2015/01/08 to 2017/12/31 for train and grid points of ten regions with highest pop as exog.



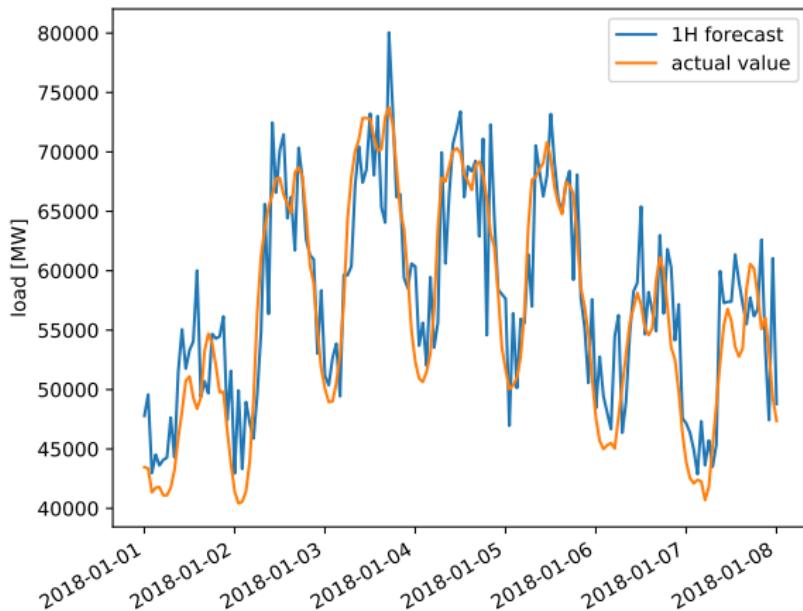
Evaluation VIII

forecast from 2017/12/31 to 2018/01/08 for ARMAX(2,2) with load data from 2015/01/08 to 2017/12/31 for train and load data shifted back in time by 1 week for same time range as exog.



Evaluation IX

Forecast from 2017/12/31 to 2018/01/08 for ARMAX(1,0) with load data from 2017/01/01 to 2017/12/31 for train and all 1435 grid points of the t2m variable as exog.



Evaluation X

ARMA/ARMAX performance using different input data and models.

1=shifted load,2=t2m mean,3=counter,4=weekend,5=top 10 regions t2m

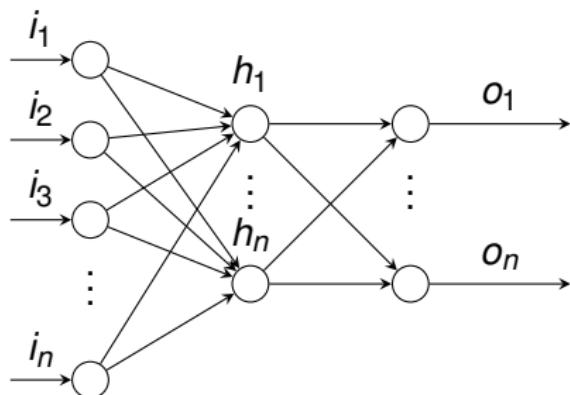
model	1	2	3	4	5	RMSE	MAE	MPE	MAPE
ARMA(1,0)	X	X	X	X	X	2621.940	1961.213	0.006	3.460
ARMA(2,2)	X	X	X	X	X	1727.742	1216.559	0.220	2.114
ARMAX(2,2)	✓	✓	X	X	X	1024.265	628.298	-0.020	1.103
ARMAX(2,2)	✓	✓	✓	X	X	1024.310	628.331	-0.006	1.103
ARMAX(2,2)	✓	✓	X	✓	X	1024.251	628.292	-0.020	1.103
ARMAX(2,2)	✓	✓	✓	✓	X	1024.295	628.324	-0.006	1.103
ARMAX(2,2)	✓	X	X	X	X	1030.753	633.436	0.101	1.112
ARMAX(2,2)	✓	X	X	✓	X	1030.756	633.433	0.101	1.112
ARMAX(2,2)	✓	X	✓	X	X	1029.191	633.093	-0.165	1.114
ARMAX(2,2)	✓	X	X	X	✓	1043.292	649.564	-0.018	1.144
ARMAX(2,2)	✓	X	✓	X	✓	1043.711	650.046	-0.012	1.145
ARMAX(2,2)	✓	✓	X	✓	✓	1051.801	659.805	-0.021	1.165
ARMAX(2,2)	✓	✓	✓	✓	✓	1051.956	660.006	-0.004	1.165
ARMAX(2,2)	✓	X	✓	X	X	1656.760	1178.435	0.021	2.043
ARMAX(2,2)	X	✓	X	X	X	1662.298	1179.187	0.185	2.039
ARMAX(2,2)	X	✓	X	✓	X	1661.909	1179.681	0.187	2.040
ARMAX(2,2)	X	✓	✓	✓	X	1656.224	1179.021	0.022	2.044
ARMAX(2,2)	X	✓	✓	✓	✓	1811.407	1321.255	0.043	2.315
ARMAX(2,2)	X	X	✓	X	✓	2004.932	1444.396	-0.036	2.547
ARMAX(2,2)	X	X	X	X	✓	2130.514	1508.978	0.211	2.663

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Conclusion

Maybe use NN, RNN? At least, mention, that redundant information of grid-based data must somehow be filtered in order to improve forecasts and speed up computation.



Acknowledgements

References I

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