Considerations for Short-Term Load Forecasting of Morocco

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Webinar with Moroccan Stakeholders

1 Introduction to Short-Term Load Forecasting

2 Short-Term Load Forecasting Methods

3 Time Series Modeling and SARIMAX

4 Results and Next Steps

Importance of Short-Term Load Forecasting (STLF)

- **Long term:**
  - Power system planning
  - Energy policy analysis.
- **Medium term:**
  - Maintenance and fuel planning
  - Energy trading.
- **Short term:**
  - Generation scheduling (hydro-thermal coordination, transaction planning,
  - Power system security
  - Economic dispatch and reliability.

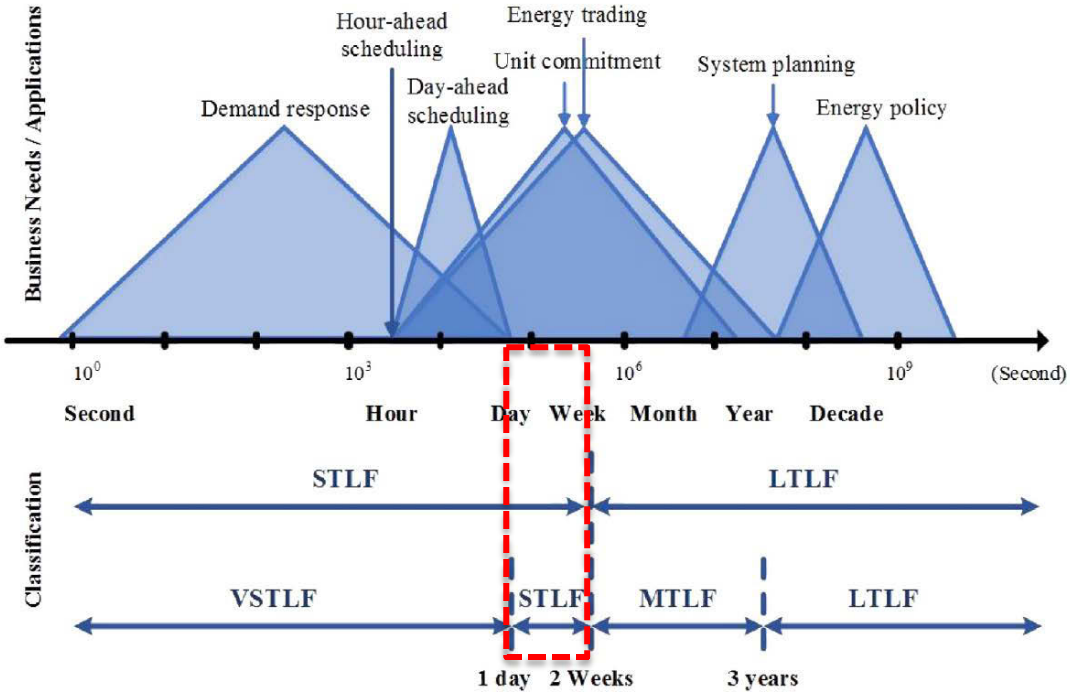


Fig.1 Load forecasting application and classification

[1] K. Hong, S. Fan, "Energy Resilience Assessment Methodology," *International journal of forecasting*, 32, p.914-938, 2016.

Data for Short-Term Load Forecasting

- Seasonal input variables:
  - Load variation from air conditioning and heating.
- Historical data:
  - Previous hour
  - Previous date
  - Same day of previous week.
- Weather forecast:
  - Temperature
  - Humidity
  - Wind
  - Cloud cover.

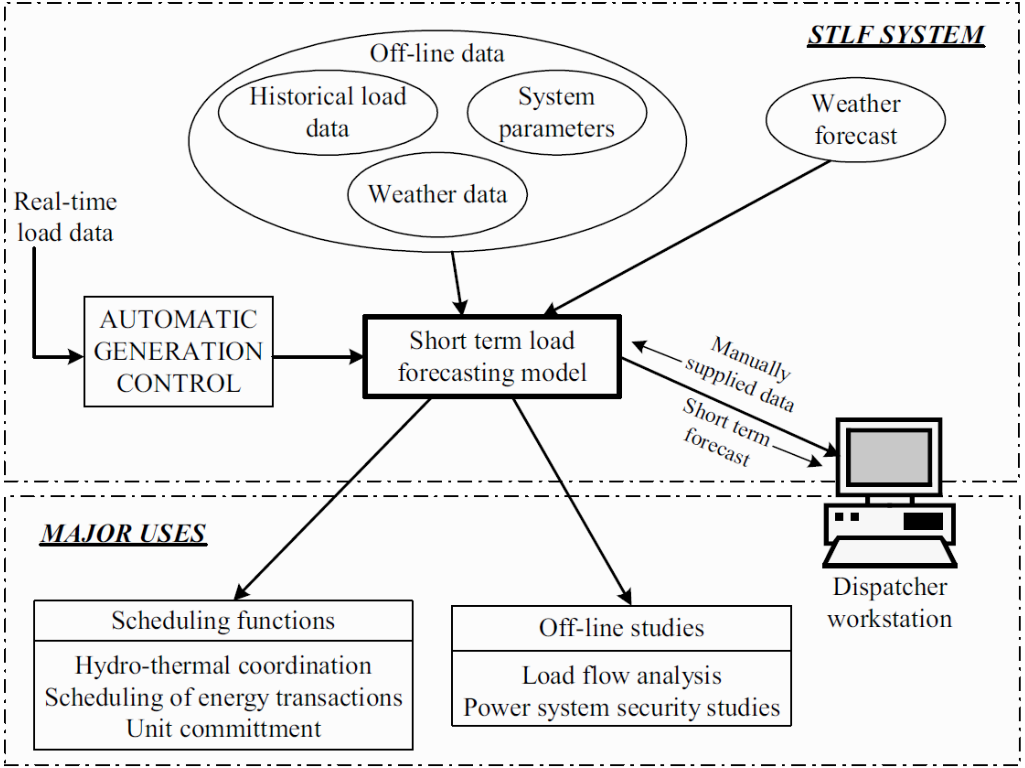


Fig.2 Input data of STLF and application of information

[2]E. Kyriakides & M. Polycarpou , “Short term electric load forecasting: A tutorial,” *Trends in Neural computation*, 16, p.391-418, 2007.

Short-Term Load Forecasting Methods

Statistical methods:

Time series statistical methods:

- Auto regressive
- Auto regressive moving average
- Auto regressive integrated moving average
- Seasonal auto regressive integrated moving average
- Seasonal auto regressive integrated moving average with exogenous variable.

Machine learning methods:

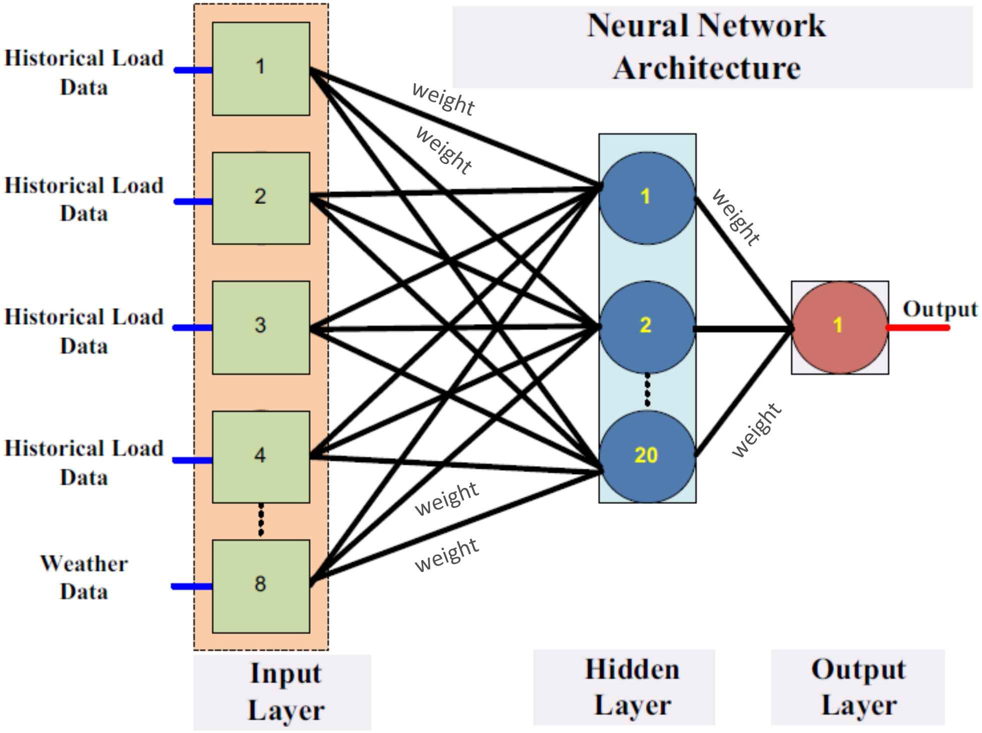
- Support vector machine
- Neural networks
- Neural networks combining with wavelet analysis
- Neural networks combining with fuzzy functions.

Short-Term Load Forecasting Methods

Artificial Neural Network

$$L_t = \mathrm{g}\left(b + \sum_{i=0}^{n} \mathrm{W}_{ji}\, L_{t-i}\right)$$

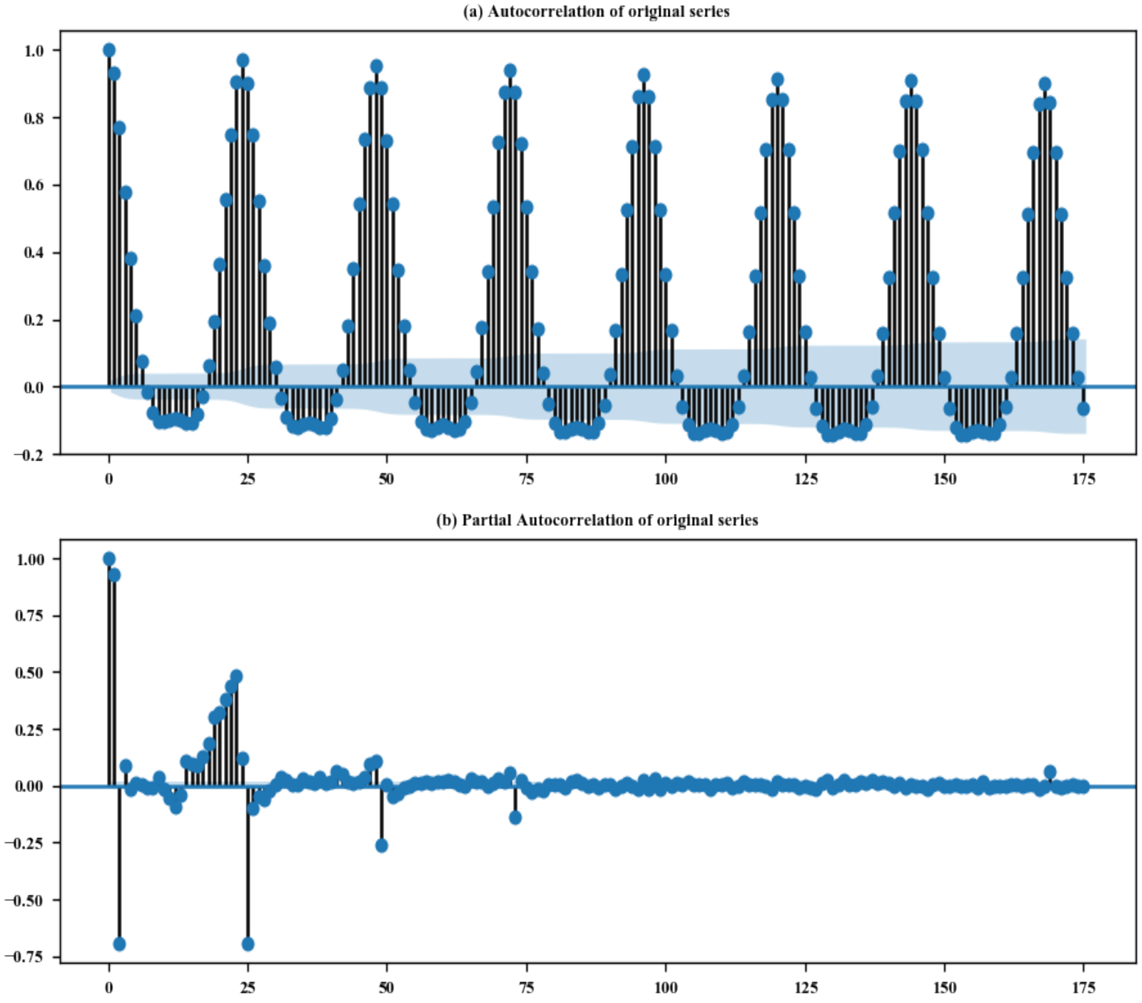
L_t: future load
L_{t-i}: past values of load
W_{ji}: weights
b : bias
g : activation function



[1] Mohammad Qamar Raza, Abbas Khosravi "A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings ," *Renewable and Sustainable Energy Reviews*, 50, p.1352-1372, 2015.

Autocorrelation (ACF) and Partial Autocorrelation (PACF)

- ACF: Correlation of a time series observations with previous time steps, called lags.
- PACF: Correlation of a time series with lags, by removing the effect of correlation due to the other lags.



Time Series Statistical Methods

$$L_t = C + \emptyset_1 L_{t-1} + \emptyset_2 L_{t-2} + .. \emptyset_p L_{t-p} + \epsilon_t$$ **AR**

$$L_t = C + \emptyset_1 L_{t-1} + .. + \emptyset_p L_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + .. + \theta_q \epsilon_{t-q}$$ **ARMA**

$$L_t = C + \sum_{i=1}^{p} \emptyset_i L_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{r} \omega_k W_k + \epsilon_t$$ **SARIMAX**

L_t: future load

C: constant

ϵ_t : forecasting error

θ_q: coefficients

W_k: exogenous variable

L_{t-i}: past values of load

$\emptyset_p$: coefficients

ϵ_{t-j}: lag forecasted error

ω_k: coefficients

Building of SARIMAX Models

SARIMAX model (*p, d, q, P,D,Q)*

- Categorize the similar pattern of days
  (working days, holidays, weekends)
- Divide the data into training set and testing set (85%, 15%)
- Build the model for given parameter values
- Guarantee the goodness of fit of model (AIC, BIC)
- Select the model based on AIC and BIC
- Automate the series using your programming language
- We use Auto.ARIMA function of pyramid.arima package of python.

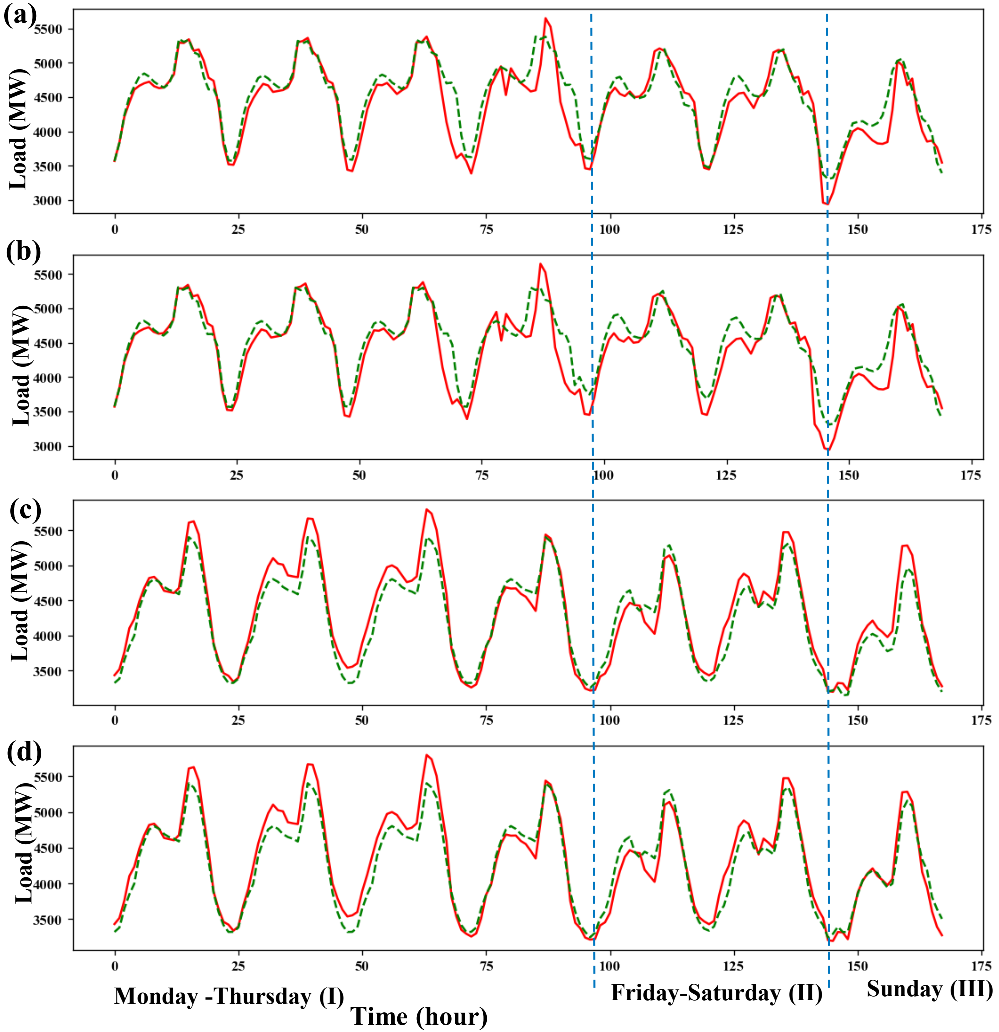
Results

Do we get higher accuracy using more information:

- Longer period of records
- Many variables.

Predicted load
Actual load

Forecast from the models from:
(a) 2015–2018 temp and load
(b) 2015–2018 load
(c) 2018 temp and load
(d) 2018 load.



* Analysis presented here based on data provided by ONEE for geographical region of Morocco

Results

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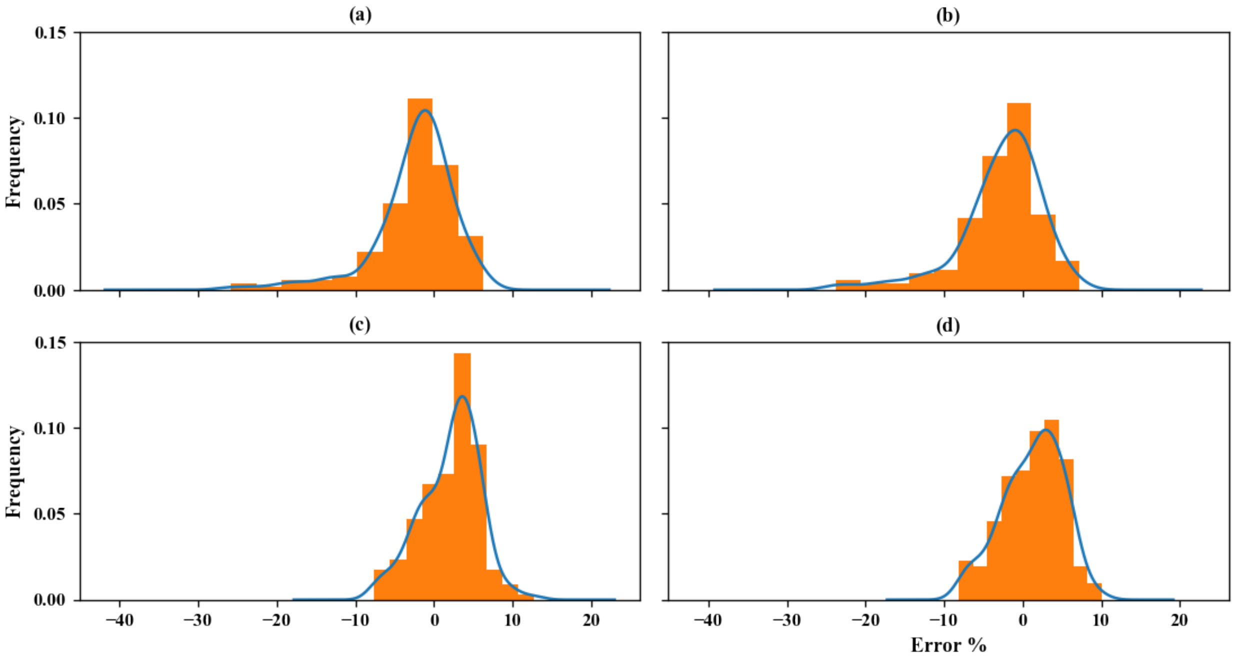

Error between actual and prediction:

(a) 2015–2018 temp and load
(b) 2015–2018 load
(c) 2018 temp and load
(d) 2018 load.

$$\text{Error} = \frac{\text{actual load-prediction}}{\text{actual load}} \%$$

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Summary and Next Steps

Summary

- Short-term load forecasting important for generator scheduling, economic dispatch, and power system security studies.
- Historical load and temperature data and time series statistical methods are used.
- Modeling results from different combination of data inform errors of peak and shape of the load profile prediction.
- Average temperatures do not improve the model prediction accuracy.

Next Steps

- Spatial forecasting is important. Spatial load and weather will provide more information.
- Behind the consumer meter data (e.g., solar net metering) correction is important in load data.
- Information of consumer behavior can be added to the models.
- Machine learning techniques also can be applied for the forecasting.

Key Points

- Short-term load forecasting is important for generator scheduling, economic dispatch, and power system security studies.
- Seasonal input variables, historical data of load, historical and forecasted weather data, and time series statistical methods and machine learning methods are used for the short-term load forecasting.
- Seasonal auto regressive integrated moving average with exogenous variable method (SARIMAX) with hourly load and temperature data used for this study.
- Three categories of days were identified, and different load and temperature past records combinations were used to build the load forecasting models.
- Long-term load records gave the better accuracy of the peak value; however, average temperature data have not improved the forecasting accuracy.
- Spatial load forecasting using regional-level load and temperature data is important.

Thank you!

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Webinar with ONEE

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