Table 2.1: Overview table of feature selection and feature engineering techniques

Author (year)	Data period location	Forecast horizon	Raw inputs	Feature engineering	Feature selection methods
Fan and Hyndman [4], (2011)	– 2004–2009 – Australia	Day-ahead for each half-hourly period	– Electricity demand – Temperature data	– Demands around the same time period for the last two days – Minimum and maximum demand in the last 24 hours – Average demand in the last seven days – Current temperature and temperatures from the last half-hour period, – Temperature change – Minimum and maximum temperature for the last 24 hours – Average temperature in the last seven days – Day of the week, holiday effect and day of the year effect	Backward elimination through cross-validation
Taieb et al. [15], (2016)	– 14/06/2009-31/12/2010 – Ireland	Day-ahead forecast for each hourly period	– 250 smart meters at 30-minute intervals – half-hourly weather data	– Calendar effects: day of the week effect, time-of-day effect, holiday effect – Temperature effects: current temperature, lagged temperatures, and summary statistics computed on lagged temperatures – Recent demand effects: lagged demand, and summary statistics computed on lagged demands	N/A
Charlton and Singleton [1] (2014)	– 1/1/2004 – 30/6/2008, – United States	– Forecast hourly loads for the entire week immediately after the 4.5 years of history – Predict hourly loads of the eight weeks missing	Hourly load and temperature data	– Temperature – Day number (to model the trend) – Day-of season terms – Seasonal terms – Public holidays	N/A
Lloyd [11] (2012)	– 1/1/2004 – 30/6/2008, – United States	– Forecast hourly loads for the entire week immediately after the 4.5 years of history – Predict hourly loads of the eight weeks missing	Hourly load and temperature data	Time of the day, time within the week, temperatures, and smoothed temperatures	N/A
Nedellec et. al. [12] (2012)	– 1/1/2004 – 30/6/2008, – United States	– Forecast hourly loads for the entire week immediately after the 4.5 years of history – Predict hourly loads of the eight weeks missing	Hourly load and temperature data	– Hour, day, month – Public holidays – Time of year: ranging from first January till the end December and scaled between 0 and 1 – Temperature and smoothed temperature	Step-wise regression through V-fold cross validation

Table 2.1: Overview table of feature selection and feature engineering techniques

Author (year)	Data period location	Forecast horizon	Raw inputs	Feature engineering	Feature selection methods
Gaillard et. al. [5] (2016)	– 1/1/2006 – 31/12/2011 – United States	One-month ahead forecast	Hourly load and temperature data	– Hour, day, month – Bank holidays and days before and after bank holidays – Time of year: ranging from first January till the end December and scaled between 0 and 1 – Smoothed temperatures and weighted average of temperatures of weather stations	TODO
Dordonnat et. al. [2] (2016)	– 1/1/2006 – 31/12/2011 – United States	One-month ahead forecast	Hourly load and temperature data	TODO	TODO
Xie [17] (2016)	– 1/1/2006 – 31/12/2011 – United States	One-month ahead forecast	Hourly load and temperature data	TODO	TODO

TABLE 2.2: Overview point load forecasting techniques

Author (year)	Period and location	Forecast horizon	Methods	Performance metric	Benchmark models
Fan and Hyndman[4] (2011)	– 2004-2009 – Australia	Day-ahead for each half-hourly period	A separate semi-parametric additive model for each half-hourly period is fitted.	MAE, MAPE, and visual inspection	Three-layer feed-forward ANN and the adaptive hybrid model from Fan and Chen [3]
Wang et al. [16] (2016)	– 2006-2011 – United States	24-hour-ahead forecasting	– Multiple linear regression – Grid search to find the optimal combination of lagged temperatures and daily moving averages	MAPE	– The multiple linear regression discussed by Hong (2010) – Modified version from the model proposed by Hong (2010) – Simplified version of the model proposed by Taieb and Hyndman using only temperature data – Daily seasonal model which used $t-24$ as forecast for the load of hour t – weekly seasonal model which uses the load of hour $t-168$ as forecast for the load of hour t
Hong et al. [8] (2014)	– 2004-2008 – United States	One day ahead and one week ahead forecasting	– Multiple linear regression, singular value decomposition, Gradient boosting, Gaussian process regression, semi-parametric regression with B-splines or cubic regression splines as smooth functions, ensemble forecasting	WRMSE	Tao's vanilla benchmark model proposed by Hong (2010)
Charlton and Singleton [1] (2014)	– 1/1/2004 – 30/6/2008 – United States	– Forecast hourly loads for the entire week immediately after the 4.5 years of history – Predict hourly loads of the eight weeks missing	– Use a combination of multiple weather stations – Multiple linear regression – Divide the data in groups and model each group separately – Outlier removal	WRMSE	The multiple linear regression discussed by Hong (2010)
Lloyd [11] (2012)	– 1/1/2004 – 30/6/2008 – United States	– Forecast hourly loads for the entire week immediately after the 4.5 years of history – Predict hourly loads of the eight weeks missing	– Gradient boosting machine – Gaussian process regression – Linear regression – Ensemble forecasting	WRMSE	The multiple linear regression discussed by Hong (2010)

Table 2.2: Overview point load forecasting techniques

Author (year)	Period and location	Forecast horizon	Methods	Performance metric	Benchmark models
Nedellec et. al. [12] (2012)	– 1/1/2004 – 30/6/2008 – United States	– Forecast the entire week immediately after the 4.5 years of history, hourly resolution – Predict hourly loads of the eight weeks missing	– Generalized additive models – Kernel regression – Random forest – Generalized Cross Validation (GCV) – V-fold cross validation – Model each hourly and zone separately	WRMSE and RMSE	The multiple linear regression discussed by Hong (2010)

Table 2.3: Overview probabilistic load forecasting techniques.

Author (year)	Period location	Forecast horizon	Methods	Performance metric	Benchmark models
Fan and Hyndman [4], (2011)	– 2004-2009 – Australia – Electricity demand	Day-ahead for each half-hourly period	Bootstrap to generate prediction intervals	Visual inspection	N/A
Taieb et al. [15], (2016)	– 14/06/2009-31/12/2010 – Ireland	Day-ahead forecast for each hourly period	Two different methods are used to forecast the probability distribution using boosted additive models: – Conditional mean and variance forecasting assuming a normal distribution – Quantile forecasting	Continuous ranked probability score (CRPS)	N/A
Liu et al. [10] (2015)	– 2006-2011 – United States	Day-ahead for each half-hourly period	Quantile regression averaging using a set of different point forecasts as input features	pinball loss function and Winkler score	– Quantiles obtained from point forecast where the lowest and highest values are set to the highest and lowest quantile respectively, the other quantiles are obtained by linear interpolation. – Adding quantiles to the point forecast by using the historical day-ahead residuals
Gaillard et. al. [5] (2016)	– 1/1/2006 – 31/12/2011 – United States	One-month ahead forecast	– Quantile regression based on pinball loss minimization – generalized additive models – Multi-horizon forecasting: One method for forecasting up to 48 h ahead and one for forecasting beyond 49 h ahead – Probabilistic temperature forecasts – Cross validation to figure out the cut-off between short and medium term forecast	Pinbll loss function	TODO
Dordonnat et. al. [2] (2016)	– 1/1/2006 – 31/12/2011 – United States	One-month ahead forecast	TODO	Pinbll loss function	TODO
Xie [17] (2016)	– 1/1/2006 – 31/12/2011 – United States	One-month ahead forecast	TODO	Pinbll loss function	TODO