Recent Survey of Electric Load Forecasting Techniques

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ABSTRACT

Electric load forecasting is considered nowadays as one of the key issues for electricity utilities to ensure both good planning and design in long-term and efficient operation and management in short and medium terms. In fact, predicting as accurately as possible the electric load and peak-load can contribute to avoiding electricity feeding disturbances and allow thus a high quality of service provided to consumers.

This paper reviews a selected set of papers on electricity demand forecasting techniques, published from 2008 to 2016. This review is intended to classify the proposed models and methods. The results presented in the surveyed papers show that a wide range of models and methods have been implemented and tested. Depending on the forecasting horizon, the study area and the used tools, the accuracy of the obtained forecasts are case-sensitive. Although classical time-series continue to be used, combined approaches involving more than two tools (models and methods) have started to attract more attention. More particularly, artificial neural networks (ANN) and swarm intelligence techniques are being increasingly used for their universal character and for the fact they do not need particular regularity of the load records.

ملخص حديث لتقنيات التنبؤ بالاحمال الكهربائية

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المُستلخص

يعتبر التنبؤ بالاحمال الكهربائية من الوسائل الاساسية التي يجب أن تتوفر للجهات المسؤولة عن قطاع الطاقة الكهربائية لتحقيق قدر مهم من جودة التخطيط على المدى البعيد و لضمان حسن التشغيل و التصرف على المدى المتوسط و القريب. يسمح التنبؤ ذو الدقة العالية بالاحمال و بالاحمال القصوى في أوقات الذروة بتجنب تذبذب التزود بالكهرباء و ضمان خدمة تزويد عملاء ذات كفاءة عالية. يهدف هذا البحث الى تقديم عرض مفصل لاخر ما تم التوصل اليه من ابحاث في مجال التنبؤ بالطلب على الكهرباء من خلال عينة منتقاة من بحوث منشورة حديثا ما بين سنتي 2008 و 2016 ميلادي. يقوم هذا البحث على تصنيف دقيق للنماذج و وسائل معايرة هذه النماذج. تم التوصل من خلال هذا البحث الى ان دقة النماذج و تقنيات التنبؤ تعتمد أساسا على نوعية و جودة البيانات المستخدمة بغرض التنبؤ و كذلك على افق التنبؤ و الوسائل المستخدمة. كما خلص البحث الى انه و على الرغم من أن تقنية السلاسل الزمنية العشوائية لازالت مستخدمة فإن التوجه العام للبحوث الحديثة يتجه الى دمج اكثر من تقنية في إطار ما يطلق عليه المقاربات المدمجة للتنبؤ. بصفة أدق، تظل الشبكات العصبية الاصطناعية و تقنيات الذكاء الاصطناعي من أفضل ما يمكن إستخدامه للتنبؤ بالطلب على الكهرباء نظرا لعدم حساسيتهما للعديد من العوامل التي من أهمها إستقرار القياسات المتوفرة للقيام بعملية التنبؤ.

Introduction

Electricity is nowadays vital for the sustainable development of nations. In fact, human life activities are conditioned by the existence of this source of energy. Since electricity can't be stored, it has to be consumed at the same time as it is produced. With the emergence of smart grid concept, better control and balance of energy supply and demand has become a necessity. A central component in a smart grid system is the forecasting of future load in different time horizons. Therefore, decision making in the electricity energy domain is mainly based on accurate forecasts. Short term load forecasting (STLF) whose prediction horizon varies from minutes to few days ahead, which is highly required for day-to-day operation of the power system, is becoming increasingly complex; On the other hand, medium term load forecasting (MTLF), where the horizon range is located between one week to several months, is essential for maintenance scheduling of the production system and fuel purchasing for turbines' operation. Long term load forecasting (LTLF), where the horizon is situated between one year to several years ahead, is applied in power generation and distribution system expansion in response to the increasing need as well as in decision making. Moreover, due to the electricity market deregulation, effective pricing policies are essentially based on LTLF. Under-estimation of the electric load in the near future can lead to power outage or eventually total blackout causing harmful danger for both human and equipments. Conversely, over estimation can lead to unnecessary produced energy, usually lost in the distribution lines and consequently this involves wasting resources.

Forecasting electricity demand is in general affected by several factors, named determinants or explanatory variables, depending on the forecasting horizon. LTLF must explicitly take into account socio-economic factors such as population growth, gross national product (GNP), total number of households, energy price index and many others. These factors are usually ignored by the STLF since they do not vary significantly in a short-time horizon. A load forecaster has to take into consideration data of the demand of previous periods as well as the meteorological explanatory variables.

Although predicting electric load is not a new field in research, some problems related to this domain are still open and researchers and forecasting practitioners are consequently still digging to find suitable solutions. Forecasting electric load is known to be notoriously difficult because of many factors including nature, quantity and quality of available related records. Forecasting electric load problem is now well-established in its theoretical findings aspect. However, designing efficient numerical algorithms for forecasting electric load is still largely open issue. Frameworks related to this problem involve several tools such as statistics, data processing, optimization, modeling tools and solving software.

A plethora of academic studies can be found in the well-known research databases. The majority of these studies lie in the field of applied research. In this study, I differentiate between models (mathematical formulation of the forecasting problem), methods (used to solve such problem) and tools (in general specific approaches or eventually commercial computer programs). In forecasting, the developed models efficiency is in general measured by a set of performance indicators such as the Mean Absolute Percentage Error ( ), the coefficient of determination ( ), the Root Mean Squared Error ( ) and the Average Absolute Relative Error ( ) defined as follows:

$$MAPE = \frac{100}{N} \sum_{t=1}^{N} \frac{|\hat{y_t} - y_t|}{\bar{y}} \quad (1)$$

$$R^2 = 1 - \frac{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}{\frac{1}{N}\sum_{t=1}^{N}(y_t - \bar{y})^2} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \quad (3)$$

$$\text{AARE} = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \quad (4)$$

where $\hat{y}_t$ is the predicted load, y_t is the t^{th} actual load, $\overline{y}$ is the mean of load demand and N is the number of observations. A good fit corresponds to low values for the MAPE, AARE and RMSE and a value of R^2 as close as possible to 1.

1. State-of-the-art of electric load forecasting techniques

In this section, a judiciously chosen sample of 41 papers published between 2008 and 2016, is reviewed. The aim here is to classify particularly the forecasting models and techniques. This survey is intended to be critical in a way that it investigates the main contributions in terms of models, solving methods, results, ease of implementation and eventual limitations.

2.1 Previous surveys

According to the four surveys (Alfares and Nazeeruddin, 2002) (Hahn et al., 2009) (Suganthi and Samuel, 2012) and (Ghalehkhondabi et al., 2016) respectively published in 2002, 2009, 2012 and 2016, a wide variety of methods and models have attracted attention. Since the survey in (Alfares and Nazeeruddin, 2002), where the load forecasting techniques were categorized into nine classes, namely, multiple regression, exponential smoothing, iterative weighted least-squares, adaptive load forecasting, stochastic time-series, ARMAX based on genetic algorithms, fuzzy logic, neural network, and knowledge based expert systems; the new trend is toward the artificial and computational intelligence methods (Hahn et al., 2009). Approaches based on Support Vector Machines (SVM) were introduced relatively recently in forecasting load. These techniques are mainly used for data classification. Hybrid approaches combining two or more different approaches have become common and are said to overcome the difficulties faced by classical time-series when they are used alone. More recently, Gray prediction models (Suganthi and Samuel, 2012) have gained popularity because they are simple and are able to operate even with limited available data. They were particularly used for LTLF. Population-based optimization techniques become increasingly used in forecasting because of their ability to operate in complex search-spaces. These classes of techniques include ant colony (AC), genetic algorithms (GA) and particle swarm optimization (PSO) (Ghalehkhondabi et al., 2016).

2.2 Time-series approaches

In recent years, time-series based approaches have continued to be used for load and peak-load forecasting (Mirowski et al., 2014) (Lydia et al., 2016) (Barak and Sadegh, 2016) (Boroojeni, 2017). A time-series model for electric load prediction is a mathematical function that describes the relationship between the load and its determinants. In general, according to Box-Jenkins methodology, the current load depends on its previous values and on the values of the external variables influencing it. A time-series model is described as follows (it is known as the Auto-Regressive Integrated Moving Average with eXogenous input (ARIMAX)):

$$\begin{aligned} y(t) = C + a_1 y(t-1) + \cdots + a_p y(t-p) + e(t) + b_1 e(t-1) + \cdots + b_q e(t-q) + c_0 u(t) \\ + c_1 u(t-1) \ldots + c_r u(t-r) \end{aligned} \quad (5)$$

where y(t) is the load at time t, u(t) is the value of the external variable at time t and e(t) is an error variable. The three components are respectively named the AR, MA and exogenous parts. All the constant coefficients are called the model coefficients. ARIMA, ARIMAX, ARMA, ARMAX, AR and ARX are special forms of stochastic time-series.

The implementation of the time-series approaches require the original data-set to be stationary (or stationarized) which is not true in large broad cases (Lydia, 2016). For forecasting the wind speed as the most important factor influencing the energy produced from wind farms, the authors in (Lydia, 2016) have introduced the concept of non-linear autoregressive models. The reported results indicate that the NLAR model outperforms the linear models because of its non-linear structure. Table 1 summarizes the surveyed papers using time-series approaches.

Table 1: Summary of the surveyed papers using time-series approaches

Reference	Purpose	Location	Determinants	Results	Advantages	Disadvantages
(Mirowski et al,2014)	STLF using 4 time-series models on aggregates of power meters in a mid-sized city based on metering infrastructure	Mid-sized city in USA	Load previous values, time of day, temperature, humidity	A MAPE that varies between 1.2% and 4.7%	Forecasting at different levels of metering and at different horizons (1h to 24h)	The time-series have to be stationary
(Lydia M. et al., 2016)	Predicting wind speed (as an electricity source) at 10-min interval based on linear and non-linear ARMA models with and without external variables	Chennai, India	Wind direction, wind shear, temperature, solar radiation	A MAPE that varies between 13.3% and 15% as means of forecasting in different horizons	Good accuracy for short time horizons	Limitation of linear models in capturing nonlinear behavior
(Boroojeni et al., 2017)	Use of multi-scale time-series in forecasting electric power demand in short and medium terms	PJM interconnection, USA	Hourly previous consumptions	A forecaster having a MAPE of 0.86% for one-hour ahead horizon	Data stationarized by logarithmic Box-Cox transformation	Original data non-stationary

2.3 Artificial Neural networks methods

A wide variety of artificial neural network (ANN) architectures have been implemented to examine the problem of predicting time-series related to electric load. ANN is known to be a good universal approximator for modeling complex systems. It is also known to capture the relationship between inputs and outputs to an arbitrary degree of accuracy. In ANN, a number of highly interconnected neurons work together in order to map some inputs to some corresponding desired outputs. The process of adjusting weight coefficients is known as "training". In ANN, the model inputs are weighted by a set of coefficients called weights and summed to a bias constant. The sum is introduced to a transfer function to generate the ANN output. This process is described by the following equation.

$$y = f(w \times u + p) \qquad (6)$$

One of the most significant drawbacks of ANN-based forecasts is that the suitable structure of the ANN, including the number of neurons in each layer, the activation functions and the training algorithms are commonly determined through trial-and-error procedure (Azadeh et al., 2014). It has been pointed out in (Wang and Shi, 2011) that improving non-linear mapping between inputs and outputs can be achieved by increasing the number of neurons in the hidden layers. Unfortunately, this can lead to increasing training time. ANN has been used in (Cam et al., 2016) coupled to data-mining techniques for data clustering to forecast demand of a supply farm. The optimal structure of the ANN has been found using genetic algorithm. The ANN training step is based on an optimization framework involving the neurons' weights as variables and the error between the forecasted and the actual electric loads as an objective function to be minimized (Sheikh and Unde, 2012) - (Buhari and Adamu, 2012). Classical training approaches such as Levenberg-Marquardt can lead to a local solution since they are based on gradient-descent algorithms. However, the ANN has the advantage of involving different variables such as type of day, time of day, temperature, humidity, total load demand (Grant et al., 2014) and special events including weekends and holidays, ANN is known to produce accurate forecasts by using high number of data and by pre-processing the data (Zadeh and Faiz, 2011). In Table 2 below, a summary of the selected papers using ANN is presented.

Table 2: Summary of the sureyed papers using ANN

Reference	Purpose	location	Determinants	results	advantages	disadvantages
(Wang and Shi, 2011)	Use of a Back-Popagation Neural Network implemented using matlab software for forecasting monthly electric power load	ZhonWei City, China	Previous monthly electric load	Error of training sample is very small but the error of testing sample is relatively high (10%)	Capturing the nonlinear aspect of the monthly load forecasting	Limited number of samples limits the forecasting accuracy
(Buhari and Adamu, 2012)	Forecasting hourly electric load	Kano substation, Nigeria	Demand of previous hours	Small MSE ($5.84e^{-6}$)	The proposed approach is simple to implement	The ANN structure is determined by trial-and-error approach which is time-consuming
(Grant et al., 2014)	STF of peak-load in a large government building using ANNs (one hour-ahead)	A governmental building in USA	Day type, time of day, humidity, total load	MAPE=3.9% Absolute maximum error (AME)= 8.2%	the developed model has taken into consideration quantitative and qualitative inputs	Bad results when using the original data
(Das, 2016)	Forecasting annual energy demand using ANN optimized by Particle Swarm Optimization (PSO) technique	Turkey	GDP, population, Import and export data	Lower MAD, MAPE, RMSE and higher R^2 compared to other approaches	The problem of non-convexity is partially solved by using a global search approach (PSO)	Optimizing the ANN weights should be non-convex

2.4 Methods combined to ANNs

To overcome the last ANN drawbacks including trial-and-error based structure definition, high training time, local solutions for the training algorithms, and data pre-processing; several techniques have been proposed such as in (El-Telbany and Al-Karmi, 2008), (Sena, 2016), (Bashir and Elhaway, 2009). The non-linear and NP-difficult problem of adjusting the ANN weights during the training phase has been declared in (El-Telbany and Al-Karmi, 2008) to be affected by the enormous amount of noise in data. Thus, the authors have proposed the PSO technique as an alternative tool for global optimization. Results show that the ANN-Forward-PSO is better than both back-propagation (BP) ANN and ARMA model in terms of mean absolute percentage error (MAPE of 2.42% in the training phase and 2.52% in the testing phase). A similar study has been conducted in (Das, 2016). The PSO-training algorithm has been enriched with random mutation operator in order to improve solution diversity and thus accelerate the convergence. Moreover, a technique has been used to remove the trend from inputs. Feature selection is applied in the study conducted in (Amjady et al., 2011) to the original time-series to filter out irrelevant and redundant candidate inputs. This operation corresponds in fact to a sort of data pre-processing. The proposed forecasting engine includes also an enhanced PSO (EPSO) known to have good global search ability to avoid the ANN weights optimization to be trapped into local minima. Similarly to the study presented in (Amjady et al., 2011), feature selection techniques has been combined to ant colony optimization (ACO), genetic algorithm and ANN to forecast hourly electric load (Sheikhan and Mohammadi, 2011). The artificial bee colony (ABC) has been used in training ANN and showed improved convergence rate while avoiding local minimum solutions (Awan et al., 2014). Wavelet transform (WT) has been applied as a data pre-processing tool. The transformed data are then introduced to a BP-ANN to forecast hourly load demand explained by load historical records and weather information (Bashir and El-Haway, 2009). In this case, the ANN has been trained by PSO to reduce the computational burden caused by the classical training algorithms such as gradient-descent or conjugate gradient-descent. A combined approach including WT, ARIMA and ANN has been developed and tested in (Voronin and Partanen, 2013) to forecast both price and demand of electricity known to influence mutually each one the other. The new idea applied consists in two steps feature selection; correlation of the inputs with the outputs and correlation between the inputs with the outputs and correlation between the inputs themselves to avoid redundancy. ARIMA is declared to detect the linear relationship and ANN is declared to capture the non-linear inputs and outputs relationship. The results of the methods combined to ANNs are summarized in Table 3 below.

Table 3: Results of the surveyed papers for the methods combined to ANNs

Reference	Method combined to ANN	Location	Determinants	Results	Advantages of the combined approach
(Amjady et al., 2011)	Wind power prediction using modified hybrid ANN and PSO	Alberta (Canada) and Oklahoma (USA)	Previous values, hour of the day	Efficient combined approach when compared to other similar approaches	Being trapped into local minima solutions has been overcome by using the global search technique (PSO) for adjusting the ANN weights

(Awan et al., 2014)	Artificial bee colony optimization (ABCO) combined to ANN for hourly electric load forecasting	Ontario State (Canada)	Calendar events, weather conditions	A MAPE average of 1.9%	The ABCO technique allows finding global minimum of the ANN weights in an efficient manner
(Bashir and El-Hawary, 2009)	Use of wavelet transform (WT), ANN and PSO for forecasting hourly load demand	Area in the state of New York, USA	Loads of previous days, temperature, wind speed, humidity	A MAPE of 2.0029%	WT is used for data transformation, ANN is used for nonlinear modeling of the load and PSO is used for the global optimization of the ANN weights
(Voronin and Partanen , 2013)	Forecasting hourly electric load demand and price using WT, ARIMA and ANN	Nordic Power Pool, Finland	Electric load of the previous hours, electricity price of the previous hours	Average of price MAPE = 5.07%, average of demand MAPE = 1.95%	WT deals with data non-stationarity, ARIMA is used for capturing the linear aspect, ANN is used to capture the nonlinear behavior.

2.5 Hybrid approaches

Hybrid approaches combining at least two techniques have been widely used in predicting electric load. PSO as generic, simple, easy to understand and implement, was in the heart of these combined approaches, e.g. (Bahrami et al., 2014), (Catalao et al., 2011), (Liu et al., 2014), (Lin et al., 2016). Three tools (among them PSO) have been tested in (Bahrami et al., 2014) for predicting hourly electric load (STLF) considering weather inputs such as mean temperature and mean relative humidity as influencing factors. The WT has been used to eliminate high frequency components from the original time-series. Grey model (GM) known to operate even with small data sets has been formulated. The resulting differential equations have been solved by an enhanced PSO algorithm. In the same direction, the work in (Catalao et al., 2011) uses combination of WT, PSO and adaptive neuro-fuzzy inference system (ANFIS) to forecast short term wind energy. A structure similar to ANN in term of layers and nodes is employed by the inference system. The coefficients of the membership functions are then optimally adjusted by PSO. A set of empirical mode decomposition (EMD) approach combined to a sub-section PSO (SS-PSO) technique have been demonstrated through experiments to be effective for STLF. In fact, the EMD is used to pre-process the original load series in such a way as to decompose it in a number of intrinsic mode functions (IMF), while avoiding the problem of mixed modes. The SS-PSO is a kind of local PSO where sub-swarms operate in specific regions of model combination weight optimization space. This approach is declared to be suitable for analyzing non-linear and non-stationary signals (Liu et al., 2014). To reduce the influence of noise-signal, the EMD technique is employed in (Chen et al., 2015). Support vector machine (SVM) optimized by PSO is used to forecast short term load with a sampling time of half hour for one week ahead. Results are declared to be accurate enough when compared to other forecasting techniques. Similar to (Chen et al., 2015), the work in (Lin et al., 2016) includes SVM, PSO and a data-mining approach to extract meaningful patterns from the original records. A summary of the surveyed papers on hybrid methods is provided in Table 4.

Table 4: Summary of the papers on hybrid methods

Reference	Hybrid approach	location	Explanatory variables	Results	Benefits of the hybridization
(Bahrami et al., 2014)	Wavelet transform (WT), Grey model (GM) and PSO for forecasting hourly STL	New York, USA	Mean temperature, mean relative humidity, mean wind speed and previous hours' loads	A MAPE that varies from 0.4598% to 5.1265% for one day ahead to 6 days ahead forecasters	WT is used to eliminate the high frequency components in the previous days' loads, the GM requires limited number of data and PSO is used to determine the coefficients of the GM
(Catalao et al., 2010)	Hybrid WT-PSO-ANFIS for STLF (hourly/day) of wind power energy	Portugal	Previous wind power series	MAPE = 4.98% Results are better than other 7 approaches. The average computation time is said to be acceptable	WT is used to decompose the wind power series into a set of better-behaved constitutive series, the future values of these series are forecasted using ANFIS and the ANFIS coefficients are optimized by PSO.
(Liu et al., 2014)	Ensemble empirical mode decomposition (EEMD) and sub-section PSO for STLF (hourly)	Chongqing, China	Previous loads, temperature, weekday	Maximum absolute error 2.0106%, average absolute error 0.5497%	The EEMD is used to decompose the original time-series into several intrinsic mode functions, the SS-PSO (multi-swarm PSO) is used to avoid local minima
(Chen et al., 2015)	Support vector machine (SVM) and PSO for STLF with half hour horizon for one week ahead	South Australia	Previous loads	A MAPE that varies from 0.92% to 3.05% for the seven day of the week and an average of 1.79%	Seasonal components have been removed and the noise signals influence reduced. The coefficients of the SVM are optimized by global search particle swarm technique.
(Lin et al., 2016)	Least-square support vector machine (LSSVM) combined to PSO for forecasting similar hour and similar day loads	Taiwan	Previous loads, temperature, humidity	MAPE between 2.40% and 3.98% for similar-day forecasting and RMSE between 1248.12 KW and 1521.09 KW	SVM is used to discover meaningful patterns in the data and PSO is used to adjust optimally the coefficients of the SVM.

2.6 Swarm intelligence techniques combined to time-series

Several time-series based approaches including auto-regressive moving average with exogenous imput (ARMAX), e.g. (Huang et al., 2008), (Wang et al., 2008), transfer function (Friedrich and Afshari, 2015), input/output model (Rahmani et al., 2013) and multiple-linear regression (MLR) (Che, 2014), have been coupled to swarm intelligence techniques such as PSO, ANN, ant colony optimization (ACO) and adaptive PSO for STLF. As example of the swarm intelligence techniques, the PSO used in forecasting is briefly described here. The forecasting model structure is defined a priori. The PSO technique is used to optimally tune the model parameters so that an error function between the forecasted loads and the actual ones is minimized. In PSO, a swarm of candidate solutions are evolved toward the optimal solution. They are respectively attracted to their personal solution discovered so far and to the solution of the best particle in the whole swarm. The mathematical formalism of the PSO technique can be found elsewhere (see (Rahmani et al., 2013) and (Saravanan et al., 2015) as examples). The common feature of all these techniques (particularly the PSO) is to adjust the coefficients of the suggested model while minimizing the error between the real loads and the predicted ones. The novelty of the approach in (Huang et al., 2008) is that it optimizes simultaneously the model orders (integer variables) and the model coefficients (real variables). A procedure dividing the problem on high discrete level and low continuous level has been applied. Unlike to the approach in (Huang et al., 2008), the model orders in (Wang et al., 2008) and (Che, 2014) had been determined by the autocorrelation function (ACF) and the partial autocorrelation function (PACF) analysis. The relationship between the forecasted load and a set of inputs is assumed to follow an S-curve and a parabola fitting law (Rahmani et al., 2013). The coefficients of this law are turned by a hybrid ACO-PSO approach to speed-up convergence. It could be noted here that the convergence problematic is rarely discussed since the majority of the proposed studies are implemented off-line. The convergence time should be important when dealing with online forecasting. A summary of the surveyed papers is presented in Table 5.

Table 5: Summary of the swarm intelligence techniques combined to time-series

Reference	Combined approach	Location	Determinants	Results	Benefits	Drawbacks
(Huang et al., 2005)	ARMAX/PSO/ hourly STLF	Taiwan	Temperature, historical records of the load	Small values of the error	Good forecasting accuracy, approach simple to implement	The model used is linear. Thus, the nonlinear features are not captured. Moreover, the PSO convergence to the optimal solution is not guaranteed.
(Friedrich and Afshari , 2015)	Transfer function (TF)/ARMA/ANN STLF up to one week (hourly forecaster)	Abudhabi city, UAE	Temperature, humidity, irradiation, wind speed	MAPE TF/PSO (1.5% to 2.5%), MAPE ANN (3.18% to 3.92%)	Weather variables are forecasted and then used in forecasting the	The ANN requires a tremendous amount of data

					load	
(Rahmani et al., 2013)	Ant Colony (AC)/PSO/S-curve/Parabola for short term forecasting of wind energy	Malaysia	Wind speed, temperature	MAPE=3.513%	The hybridization of the ACO and the PSO has led to good accuracy and faster convergence profile	Since the ACO and PSO exchange the best solutions, they will be mutually influenced by the drawbacks of each one taken separately (premature convergence of PSO and local search for the ACO)
(Che, 2014)	Multiple linear regression (MLR)/SVR/Adaptive PSO (APSO) for hourly STLF	California	Previous hourly loads	Maximum MAPE of 3.5%	Interpretability of seasonal cycles and good accuracy achievement. APSO is used to tune the parameters of the SVM.	The outlined quadratic programming problem is difficult to solve. The obtained solutions are sub-optimal.

2.7 Econometric models

LTLF usually involves socio-economic indicators including population, per capita Gross Domestic Product (GDP), import-export data, the number of subscribers and other cultural factors. In the literature, this problem has been tackled using econometric models, e.g. (Saravannan et al., 2015), (Nazari et al., 2015), (Kiran et al., 2012), (Al-Rahidi and El-Naggar, 2010). In this review, I will focus on approaches involving swarm intelligence techniques (more particularly the PSO). For forecasting electricity consumption in India, the authors in (Saravanan et al., 2015) used an exponential model known to operate efficiently in the case of non-linear data. The structure of the model is imposed in advance. The forecasting task consists in adjusting the model coefficients using PSO technique. The available data have been divided into model training and testing. The calibrated model has been used to predict the annual electricity demand in India up to the year 2025. A 'pragmatic' methodology that can be used as a generic tool to calibrate electric load demand models at any level (hourly, daily, weekly, monthly or yearly) has been developed in (Almeshaiei and Soltan, 2011) based on the decomposition and segmentation of time-series. Two classes of econometric models (exponential and linear) have been used to predict annual energy demand for both residential and commercial sectors of Iran based on the added value of the two sectors such as value of made buildings, population and the electrical and fuel appliance price index (Nazari et al., 2015). The optimization task was performed using PSO and GA. Many scenarios have been evaluated using statistical performance measures. In my opinion, the main drawback of this approach consists on how to define the model coefficients search-space limits even though this can be explained by the robustness of the optimization method. Since the majority of forecasting methods concentrate on accuracy, the approach in (Jun and Ergun, 2011) focuses on simplicity. Thus, it can be concluded that it would be better to sacrifice an amount of accuracy to achieve feasibility. Simple regression models using the similar day input have been tried successfully. Prior to the work in (Nazari et al., 2015), authors in (Kiran et al., 2012) have applied PSO and ACO to calibrate annual linear and quadratic models for forecasting electric load in Turkey. The quadratic model (sometimes named bilinear) has been found to perform better in terms of accuracy. The authors didn't indicate the way in which they fixed the search-space limits of the model coefficients. The econometric model has been implemented using different variants of the PSO algorithm to forecast the annual electric load consumption in Iran (Askarzadeh, 2014) Genetic programming (GP) combined with curve fitting were used for the case study of India to LTLF (Behera et al., 2014) Linear and non-linear regressions have been used to forecast annual electricity consumption in Kuwait. The model coefficients have been tuned successfully by PSO. Results are said to be accurate (Al-Rahidi and El-Naggar, 2010). A summary of the results of the studies using the econometric models is provided in Table 6.

Table 6: Results of the surveyed papers using the econometric models

Reference	Model/Method	location	Determinants	results	Advantages
(Saravanan et al., 2015)	Exponential model/PSO	India	Population, GDP, import-export data	MAPE = 2.6102%	Accurate forecaster although the data are nonlinear
(Almeshaiei and Soltan, 2011)	Decomposition and segmentation of the load time-series	Kuwait	Historical records of the load	95% of confidence for the fitted polynomial plot	Guideline for forecasting daily electric load
(Jun and Ergun, 2011)	Simple regression based method/Least-Mean-Square (LMS) algorithm for daily STLF	New England, USA	Previous daily load records	MAPE = 2.1%	The proposed approach ensures a certain level of balance between accuracy and ease of use.
(Kiran, 2012)	PSO/ACO for annual load forecasting	Turkey	GDP, population, import, export	Deviation is 3.37% for the linear model and -2.77% for the quadratic model	The PSO handles the continuous parameters of the models and the ACO handles the discrete ones.
(Behera et al., 2014)	Curve fitting/Genetic Programming (GP) for LTLF (annual)	India	Annual demand previous data	An error of 0.00106% for the GP model	Results are better than other approaches and the proposed technique is simple
(Alrashidi and El-Naggar, 2010)	Regression (linear and quadratic) model/PSO for annual peak-load forecasting	Kuwait Egypt	Records of annual peak-loads	Best average error obtained for the quadratic model is of 1.3336%	Proposed approach simple to implement and provides good results

Conclusion

In this survey paper, models and methods used for electric load forecasting included in a selected set of papers published between 2008 and 2016 have been reviewed. These approaches have been classified into seven categories, namely, time-series (TS), artificial neural networks (ANN), methods combined to ANN, hybrid approaches, swarm intelligence combined to time series and econometric approaches. Due to the limitations of some approaches, combined and hybrid approaches have gained the attention of the electric load forecasting practitioners and researchers. The level of accuracy is highly case-sensitive depending on the case study, the available records, and the used tools. The recent approaches are concentrating on ensuring a certain level of trade-off between accuracy and feasibility.

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