# 1

# Overview of Building Energy Analysis

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## 1.1. Introduction

In Europe, buildings account for 40% of total energy use and 36% of total $CO_2$ emission [EUR 10]. Figure 1.1 shows the annual energy consumption of each sector over 20 years from 1990 to 2009 in France. The part of industry decreased from 30% to 25%, and that of transport was stable around 30%. However, the usage of residential tertiary increased from 37% to 41%. We can see an increasing ratio of the building energy consumption during these years, and we can expect that the ratio will continue to increase in the future. The prediction of energy use in buildings is therefore significant for improving the energy performance of buildings, leading to energy conservation and reducing environmental impact.

However, the energy system in buildings is quite complex, as the energy types and building types vary greatly. In the literature, the main energy forms considered are heating/cooling loads, hot water and electricity consumption. The most frequently considered building types are offices, residential and engineering buildings, varying from small rooms to big estates. The energy behavior of a building is influenced by many factors, such as weather conditions, especially the dry bulb temperature, building construction and thermal property of the physical materials used, occupants and their behavior, sublevel components such as heating, ventilating and air conditioning (HVAC), and lighting systems.

Due to the complexity of the energy system, accurate consumption prediction is quite difficult. In recent years, a large number of approaches for this purpose, either elaborate or simple, have been proposed and applied to a broad range of problems. This research work has been carried out in the process of designing new buildings, operation or retrofit of contemporary buildings, varying from a building's subsystem analysis to regional or national level modeling. Predictions can be performed on the whole building or sublevel components by thoroughly analyzing each influencing factor or approximating the usage by considering several major factors. An effective and efficient model has always been the goal of the research and engineering community.

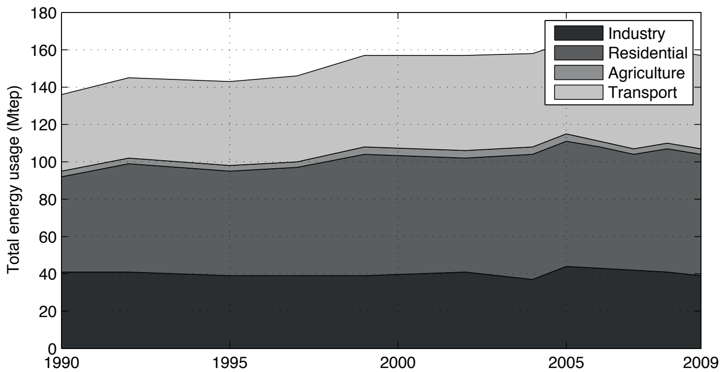


**Figure 1.1.** *Annual energy consumption in each sector of France (source: [COM 11])*

The following sections review the recent work related to the modeling and prediction of building energy consumption (more details can be found in [ZHA 12b] and reference therein). The methods used in this application include engineering, statistical and artificial intelligence methods. The most widely used artificial intelligence methods are artificial neural networks (ANNs) and support vector machines (SVMs). In 2003 and 2010, Krarti and Dounis provided two overviews of artificial intelligence methods in the application of building energy systems [KRA 03, DOU 10]. The following chapters of this book especially focus on the prediction applications. To even further enrich the content and provide the readers with a complete view of various prediction approaches, this section also reviews engineering and statistical methods. Moreover, there are also some hybrid approaches that combine some of the above models to optimize predictive performance (see [YAO 05, WAN 06, KAR 06] [LIA 07]). In the following, we describe the problems, models, related problems, such as data pre-/postprocessing, and the comparison of these models.

## 1.2. Physical models

The engineering methods use physical principles to calculate thermal dynamics and energy behavior for the whole building level or for sublevel components. They have been adequately developed over the past 50 years. These methods can be roughly classified into two categories, the detailed comprehensive methods and the simplified methods. The comprehensive methods use very elaborate physical functions or thermal dynamics to calculate precisely, step by step, the energy consumption for all components of the building with the building's and environmental information, such as external climate conditions, building construction, operation, utility rate schedule and HVAC equipment, as the inputs. In this section, we concentrate on the global view of models and applications, while the details of these computational processes are far beyond the purpose of this chapter. Readers may refer to [CLA 01] for more details. For HVAC systems, in particular, the detailed energy calculation is introduced in [MCQ 05]. The International Organization for Standardization (ISO) has developed a standard for the calculation of energy use for space heating and cooling for a building and its components [ISO 08].

Hundreds of software tools have been developed for evaluating energy efficiency, renewable energy, and sustainability in buildings, such as DOE-2, EnergyPlus, BLAST and ESP-r [SIM 11]. Some of them have been widely used for developing building energy standards and analyzing energy consumption and conservation measures of buildings. Surveys of these tools are performed in [ALH 01, CRA 08]. For readers' information, the U.S. Department of Energy (DOE) maintains a list of almost all the energy simulation tools [SIM 11], which is constantly updated.

Although these elaborate simulation tools are effective and accurate, in practice, there are some difficulties. Since these tools are based on physical principles, to achieve an accurate simulation, they require details of building and environmental parameters as input data. On the one hand, these parameters are unavailable to many organizations, for instance, the information on each room in a large building is always difficult to obtain. This lack of precise inputs will lead to a low accurate simulation. On the other hand, operating these tools normally requires tedious expert work, making it difficult to perform. For these reasons, some researchers have proposed simpler models to offer alternatives to certain applications.

Al-Homoud [ALH 01] reviewed two simplified methods. One is the degree day method in which only one index, degree day, is analyzed. This steady-state method is suitable for estimating small buildings' energy consumption where the envelope-based energy dominates. The other one is bin, also known as the temperature frequency method, which can be used to model large buildings where internally generated loads dominate or loads are not linearly dependent on outdoor/indoor temperature difference.

Weather conditions are important factors to determine building energy usage. These take many forms, such as temperature, humidity, solar radiation and wind speed, and vary over time. Certain studies are conducted to simplify weather conditions in building energy calculations. White and Reichmuth [WHI 96] attempted to use average monthly temperatures to predict monthly building energy consumption. This prediction is more accurate than standard procedures, which normally use heating and cooling degree days or temperature bins. Westphal and Lamberts [WES 04] predicted the annual heating and cooling load of non-residential buildings simply based on some weather variables, including monthly average of maximum and minimum temperatures, atmospheric pressure, cloud cover and relative humidity. Their results showed good accuracy on low mass envelope buildings, compared to elaborate simulation tools such as ESP, BLAST and DOE2.

As well as weather conditions, the building characteristic is another important yet complex factor in determining energy performance.

Yao and Steemers [YAO 05] developed a simple method of predicting a daily energy consumption profile for the design of a renewable energy system for residential buildings. The total building energy consumption was defined as the summation of several components: appliances, hot water and space heating. For each component, a specific modeling method was employed. For instance, to model electric appliances, they used the average end-use consumption from large amounts of statistical data. While modeling space heating demand, a simplified physical model was applied. Since the average value varies seasonally, this method predicts energy demand for one season at a time.

By adopting this divide-and-sum concept, Rice *et al.* [RIC 10] simplified each sublevel calculation to explain the system level building energy consumption. In the project "Updating the ASHRAE/ACCA Residential Heating and Cooling Load Calculation Procedures and Data" (RP-1199), Barnaby and Spitler [BAR 05b] proposed a residential load factor method, which is a simple method and can be done by hand. The load contributions from various sources were evaluated separately and then added up. Wang and Xu [WAN 06] simplified the physical characteristics of buildings to implement the prediction. For building envelopes, the model parameters were determined by using easily available physical details based on the frequency characteristic analysis. For various internal components, they used a thermal network of lumped thermal mass to represent the internal mass. A genetic algorithm was used to identify model parameters based on operation data. Yik *et al.* [YIK 01] used detailed simulation tools to obtain cooling load profiles for different types of buildings. A simple model, which is a combination of these detailed simulation results, was proposed to determine the simultaneous cooling load of a building.

Calibration is another important issue in building energy simulation. By tuning the inputs carefully, simulation can match the simulated energy behavior precisely with that of a specific building in reality. Pan *et al.* [PAN 07] summarized the calibrated simulation as one building energy analysis method and applied it to analyze the energy usage of a high-rise commercial building. After several repeated calibration steps, this energy model showed high accuracy in predicting the actual energy usage of the specified building. A detailed review of calibration simulation is provided in [RED 06]. Since calibration is a tedious and time-consuming work, we can see that doing accurate simulation using a detailed engineering method is of high complexity.

We note that there is no apparent boundary between the simplified and elaborate models. It is also possible to do simplified simulation with some comprehensive tools, such as EnergyPlus [CRA 01]. As suggested by AI-Homoud [ALH 01], if the purpose is to study trends, compare systems or alternatives, then simplified analysis methods might be sufficient. In contrast, for a detailed energy analysis of buildings and subsystems and lifecycle cost analysis, more comprehensive tools will be more appropriate [ALH 01].

## 1.3. Gray models

When the information of one system is partially known, we call this system a gray system. The gray model can be used to analyze building energy behavior when there is only incomplete or uncertain data.

In 1999, Wang *et al.* [WAN 99] applied a gray model to predict the building heat moisture system. The predicting accuracy is fairly high. Guo *et al.* [GUO 11] used an improved gray system to predict the energy consumption of heat pump water heaters in residential buildings. They evaluated the influence of a data sample interval in the prediction accuracy and found that the best interval is 4 weeks. This model requires little input data and the prediction error is within a normal range. Zhou *et al.* [ZHO 08] did on-line prediction of the cooling load by integrating two weather prediction modules into a simplified building thermal load model, which is developed in [WAN 06]: one is the temperature/relative humidity prediction, which is achieved by using a modified gray model, the other is solar radiation prediction, which is achieved using a regression model. Experimental results showed that the performance of the simplified thermal network model is improved as long as the predicted weather data from the first module are used in the training process.

## 1.4. Statistical models

Statistical models have been widely considered for building energy, including regression models, such as autoregressive model with eXtra inputs (ARX), autoregressive integrated moving average (ARIMA), autoregressive integrated moving average with eXtra inputs (ARIMAX) and conditional demand analysis (CDA).

Statistical regression models simply correlate the energy consumption or energy index with the influencing variables. These empirical models are developed from historical performance data, which means that before training the models, we need to collect enough historical data. Much research on regression models has been carried out on the following problems. The first is to predict the energy usage over simplified variables such as one or several weather parameters. The second is to predict a useful energy index. The third one is to estimate important parameters of energy usage, such as total heat loss coefficient, total heat capacity and gain factor, which are useful in analyzing thermal behavior of building or sublevel systems.

In some simplified engineering models, the regression is used to correlate energy consumption with the climatic variables to obtain an energy signature [BAU 98, WES 99, PFA 05]. Bauer and Scartezzini [BAU 98] proposed a regression method to handle both heating and cooling calculations simultaneously by dealing with internal as well as solar gains. Ansari *et al.* [ANS 05] calculated the cooling load of a building by adding up the cooling load of each component of the building envelope. Each sublevel cooling load is a simple regression function of temperature difference between inside and outside. Dhar *et al.* [DHA 98, DHA 99] modeled heating and cooling load in commercial buildings with outdoor dry bulb temperature as the only weather variable. A new temperature-based Fourier series model was proposed to represent nonlinear dependence of heating and cooling loads on time and temperature. If humidity and solar data are also available, they suggested using the generalized Fourier series model since it has more engineering relevance and higher prediction ability. Also considering dry bulb temperature as the single variable for model developing, Lei and Hu [LEI 09] evaluated regression models for predicting energy savings from retrofit projects of office buildings in a hot summer and cold winter region. They showed that a single variable linear model is sufficient and practical to model the energy use in hot and cold weather conditions. Ma *et al.* [MA 10] integrated multiple linear regression and self-regression methods to predict monthly power energy consumption for large-scale public buildings. In the work of Cho *et al.* [CHO 04], the regression model was developed on 1 day, 1 week and 3 month measurements, leading to the prediction error in the annual energy consumption of 100%, 30% and 6%, respectively. These results show that the length of the measurement period strongly influences the temperature-dependent regression models.

Concerning the prediction of the energy index, Lam *et al.* [LAM 10] used principle component analysis (PCA) to develop a climatic index $Z$ with regard to global solar radiation and dry and wet bulb temperature. They found that $Z$ has the same trend as simulated cooling load, HVAC, and building energy use. This trend was obtained from the analysis of correlation by a linear regression analysis. The model was developed based on the data from 1979 to 2007. Ghiaus [GHI 06] developed a robust regression model to correlate the heating loss on the dry bulb temperature by using the range between the first and the third quartile of the quantile–quantile plot, which gives the relation of these two variables.

Jiménez and Heras [JIM 05] used ARX to estimate the $U$ and $g$ values of building components. Kimbara *et al.* [KIM 95] developed an ARIMA model to implement on-line prediction. The model was first derived on the past load data, and was then used to predict load profiles for the next day. ARIMAX model has also been applied to some applications, such as predicting and controlling the peak electricity demand for commercial buildings [HOF 98] and predicting the power demand of the buildings [NEW 10]. In [NEW 10], Newsham and Birt put a special emphasis on the influence of occupancy, which can apparently increase the accuracy of the model.

Aydinalp-Koksal and Ugursal [AYD 08] suggested considering a regression-based method, called CDA, when we predict national level building energy consumption. In their experimental comparisons, CDA showed accurate predicting ability as good as neural networks and engineering methods, but that was easier to develop and use. However, the drawback of the CDA model was the lack of detail and flexibility, and it required a large amount of input information. CDA was also employed in the early work for analyzing residential energy consumption [LAF 94].

## 1.5. Artificial intelligence models

### 1.5.1. *Neural networks*

ANNs are the most widely used artificial intelligence models in the application of building energy prediction. This type of model is good at solving nonlinear problems and is an effective approach to this complex application. In the past 20 years, researchers have applied ANNs to analyze various types of building energy consumption in a variety of conditions, such as heating/cooling load, electricity consumption, sublevel components operation and optimization, and estimation of usage parameters. In this section, we review some past research and put them into groups according to the applications dealt with. Additionally, model optimization, such as the preprocessing of input data and comparisons between ANNs and other models, are highlighted at the end.

In 2006, Kalogirou [KAL 06] made a brief review of the ANNs in energy applications in buildings, including solar water heating systems, solar radiation, wind speed, air flow distribution inside a room, prediction of energy consumption, indoor air temperature and HVAC system analysis.

Kalogirou *et al.* [KAL 97] used back propagation neural networks to predict the required heating load of buildings. The model was trained on the consumption data of 225 buildings, which vary largely from small spaces to big rooms. Ekici and Aksoy [EKI 09] used the same model to predict building heating loads in three buildings. The training and testing datasets were calculated by using the finite difference approach of transient state one-dimensional heat conduction. Olofsson *et al.* [OLO 98] predicted the annual heating demand of a number of small single family buildings in the north of Sweden. Later, Olofsson and Andersson [OLO 01] developed a neural network that makes long-term energy demand (the annual heating demand) predictions based on short-term (typically from 2 to 5 weeks) measured data with a high prediction rate for single family buildings.

In [YOK 09], Yokoyama *et al.* used a back propagation neural network to predict cooling demand in a building. In their work, a global optimization method called modal trimming method was proposed for identifying model parameters. Kreider *et al.* [KRE 95] reported results of a recurrent neural network on hourly energy consumption data to predict building heating and cooling energy needs in the future, knowing only the weather and time stamp. Based on the same recurrent neural network, Ben-Nakhi and Mahmoud [BEN 04] predicted the cooling load of three office buildings. The cooling load data from 1997 to 2000 was used for model training and the data for 2001 was used for model testing. Kalogirou [KAL 00] used neural networks for the prediction of the energy consumption of a passive solar building where mechanical and electrical heating devices are not used. Considering the influence of weather on the energy consumption in different regions, Yan and Yao [YAN 10] used a back propagation neural network to predict a building's heating and cooling load in different climate zones represented by heating degree day and cooling degree day. The neural network was trained with these two energy measurements as parts of input variables.

In the application of building electricity usage prediction, an early study [JOI 92] has successfully used neural networks for predicting hourly electricity consumption as well as chilled and hot water for an engineering center building. Nizami and Al-Garni [JAV 95] tried a simple feed-forward neural network to relate the electric energy consumption to the number of occupants and weather data. González and Zamarreño [GON 05] predicted short-term electricity load with a special neural network, which feeds back part of its outputs. In contrast, Azadeh *et al.* [AZA 08] predicted the long-term annual electricity consumption in energy intensive manufacturing industries and showed that the neural network is very applicable to this problem when energy consumption shows high fluctuation. Wong *et al.* [WON 10] used a neural network to predict energy consumption for office buildings with day-lighting controls in subtropical climates. The outputs of the model include daily electricity usage for cooling, heating, electric lighting and total building.

ANNs are also used to analyze and optimize sublevel components' behavior, mostly for HVAC systems. Hou *et al.* [HOU 06a] predicted air conditioning load in a building, which is a key to the optimal control of the HVAC system. Lee *et al.* [LEE 04] used a general regression neural network to detect and diagnose faults in a building's air handling unit. Aydinalp *et al.* [AYD 02] showed that the neural network can be used to estimate appliance, lighting and space cooling (ALC) energy consumption, and it is also a good model to estimate the effects of the socioeconomic factors on this consumption in the Canadian residential sector. In their follow-up work, neural network models were developed to successfully estimate the space and domestic hot water heating energy consumptions in the same sector [AYD 04].

In [BEN 02] [BEN 04], general regression neural networks were used for air conditioning set-back controlling, and for optimizing HVAC thermal energy storage in public and office buildings. Yalcintas *et al.* [YAL 05] used neural networks to predict chiller plant energy use of a building in a tropical climate. Later, they used a three-layer feed-forward neural network to predict energy savings in an equipment retrofit [YAL 08]. Gouda *et al.* [GOU 02] used a multilayered feed-forward neural network to predict internal temperature with easily measurable inputs, which include outdoor temperature, solar irradiance, heating valve position and the building indoor temperature.

Building energy performance parameters can be estimated by neural networks. In [OLO 99, OLO 02, LUN 02, LUN 04], the authors estimated the total heat loss coefficient, the total heat capacity and the gain factor, which are important for a reliable energy demand forecast. The method is based on an analysis of a neural network model that is trained on simple data, the indoor/outdoor temperature difference, the supplied heat and the available free heat. Kreider *et al.* [KRE 95] reported results of recurrent neural networks on hourly energy consumption data. They also reported results on finding the thermal resistance, $R$, and thermal capacitance, $C$, for buildings from networks trained on building data. Zmeureanu [ZME 02] proposed a method using the general regression neural networks to evaluate the coefficient of performance of existing rooftop units. Yalcintas presented an ANN-based benchmarking technique for building energy in tropical climates, focused on predicting a weighted energy use index. The selected buildings are of a wide variety [YAL 06, YAL 07].

The input data for the model training can be obtained from on-site measurement, survey, billing collection or simulation. The raw data may have noisy or useless variables, therefore it can be cleaned and reduced before model development. There is much research concerning the data preprocessing technologies. González and Zamarreño [GON 05] predicted short-term electricity load by using two phases of neural networks. The first layer predicts climatic variables, while the second predicts energy usage, which takes the outputs of the first layer as inputs. The same two-phase technology was also used by Yokoyama *et al.* in predicting cooling load [YOK 09]. The trend and periodic change were first removed from data, and then the converted data was used as the main input for the model training. Additional inputs, including air temperature and relative humidity, were considered to use predicted values. Their effects on the prediction of energy demand were also investigated in this work.

Ben-Nakhi and Mahmoud [BEN 04] predicted the cooling load profile of the next day, and the model was trained on a single variable, outside dry bulb temperature. Ekici and Aksoy [EKI 09] predicted building heating loads without considering climatic variables. The networks were trained by only three inputs, transparency ratio, building orientation and insulation thickness. Kreider and Haberl [KRE 94] predicted the nearest future with the input of nearest past data. For predicting far future, they used recurrent neural networks. Yang *et al.* [YAN 05] used accumulative and sliding window methods to train neural networks for the purpose of on-line building energy prediction. Sliding windows constrained input samples in a small range.

Olofsson *et al.* [OLO 98] used PCA to reduce the variable dimension before predicting the annual heating demand. In their later work, they achieved long-term energy demand prediction based on short-term measured data [OLO 01]. Kubota *et al.* [KUB 00] used a genetic algorithm for the variable extraction and selection on measured data, and then fuzzy neural networks were developed for the building energy load prediction. Here, the variable extraction means translating original variables into meaningful information that is used as input in the fuzzy inference system. Hou *et al.* [HOU 06a] integrated rough sets theory and a neural network to predict an air conditioning load. Rough sets theory was applied to find relevant factors influencing the load, which were used as inputs in a neural network to predict the cooling load. Kusiak *et al.* [KUS 10] predicted the daily steam load of buildings by a neural network ensemble with five multilayer perceptrons (MLPs) methods since, in several case studies, it outperforms nine other data mining algorithms, including classification and regression trees (CART), CHAID, exhaustive Chi-squared automatic interaction detection (CHAID), boosting tree, multivariate adaptive regression (MARS) splines, random forest, SVM, MLP and k-nearest neighbors (k-NN). A correlation coefficient matrix and the boosting tree algorithm were used for variable selection. Karatasou *et al.* [KAR 06] studied how statistical procedures can improve neural network models in the prediction of hourly energy loads. The statistical methods, such as hypothesis testing, information criteria and cross validation, were applied in both input preprocessing and model selection. Experimental results demonstrated that the accuracy of the prediction is comparable to the best results reported in the literature.

The outputs of neural networks may not be exactly what we expected; Kajl *et al.* proposed a fuzzy logic to correct the outputs by postprocessing the results of neural networks. The fuzzy assistant allows the user to determine the impact of several building parameters on the annual and monthly energy consumption [KAJ 96, KAJ 97].

Some comparisons between neural network and other prediction models were performed in the literature. Azadeh *et al.* [AZA 08] showed that the neural network was very applicable to the annual electricity consumption prediction in manufacturing industries where energy consumption has a high fluctuation. It is superior to the conventional nonlinear regression model through analysis of variance. Aydinalp *et al.* [AYD 02] showed that neural networks can achieve higher prediction performance than engineering models in estimating ALC energy consumption and the effects of socioeconomic factors on this consumption in the Canadian residential sector. Later, ANN was compared with the CDA method in [AYD 08]. From this work, we see that CDA has a high ability to solve the same problem as the ANN model, while the former is easier to develop and use. Neto [NET 08] compared the elaborate engineering method with neural network model for predicting building energy consumption. Both models have shown high prediction accuracy, while ANN is slightly better than the engineering model in the short-term prediction.

### 1.5.2. *Support vector machines*

SVMs are increasingly used in research and industry. They are highly effective models in solving nonlinear problems even with small quantities of training data. Many studies of these models were conducted on building energy analysis in the past 5 years.

Dong *et al.* [DON 05a] first applied SVMs to predict the monthly electricity consumption of four buildings in the tropical region. Three-year data were trained and the derived model was applied to 1-year data to predict the landlord utility in that year. The results showed good performances of SVMs on this problem.

Lai *et al.* [LAI 08] applied this model on 1-year electricity consumption of a building. The variables include climate variations. In their experiments, the model was derived from 1-year performance and then tested on 3-month behavior. They also tested the model on each daily basis dataset to verify the stability of this approach during short periods. In addition, they added perturbation manually to a certain part of the historical performance and used this model to detect the perturbation by examining the change in the contributing weights.

Li *et al.* [LI 09] used SVMs to predict the hourly cooling load of an office building. The performance of the support vector regression is better than the conventional back propagation neural networks. Hou and Lian [HOU 09] also used SVMs for predicting the cooling load of the HVAC system. The result shows that SVMs are better than the ARIMA model.

Li *et al.* [LI 10a] predicted the annual electricity consumption of buildings by back propagation neural networks, radial basis function neural networks, general regression neural networks and SVMs. They found that general regression neural networks and SVMs were more applicable to this problem compared to other models. Furthermore, SVM showed the best performance among all prediction models. The models were trained on the data of 59 buildings and tested on nine buildings.

Liang and Du [LIA 07] presented a cost-effective fault detection and diagnosis method for HVAC systems by combining the physical model and a SVM. By using a four-layer SVM classifier, the normal condition and three possible faults can be recognized quickly and accurately with a small number of training samples. Three major faults are recirculation damper stuck, cooling coil fouling/block and supply fan speed decreasing. The indicators are the supply and mixed air temperatures, the outlet water temperature and the valve control signal.

Research was performed for pre- or postprocess model training. Lv *et al.* [LV 10] used PCA to reduce variables before training SVMs for predicting building cooling load. Li *et al.* [LI 10c] used an improved PCA, called kernel principal component analysis, before training SVMs to predict building cooling load. Li *et al.* [LI 10b] used a fuzzy C-mean clustering algorithm to cluster the samples according to their degree of similarity. Then, they applied a fuzzy membership to each sample to indicate its contribution to the model. In the postprocessing, Zhang and Qi [ZHA 09] applied Markov chains to do further interval forecasting after prediction of building heating load by SVMs.

## 1.6. Comparison of existing models

From the above description and analysis, it is obvious that a large number of calculations are needed to evaluate the building energy system, from subsystems to building level and even regional or national level. The reviewed research work is briefly summarized in Table 1.1, distinguished by considered problems and models, where we have omitted engineering methods because many of them can solve all of the problems. Each model has its own advantages in certain cases of applications.

| Problems | Statistical | ANNs | SVMs |
|---|---|---|---|
| Heating/Cooling | [BAU 98, ANS 05] [DHA 99, DHA 98] | [KAL 97, EKI 09, OLO 98] [OLO 01, YAN 10, YOK 09] [KRE 95, BEN 04, KAL 00] | [LI 09, HOU 09] [LV 10, ZHA 09] |
| Electricity | [MA 10, HOF 98] [AZA 08, NEW 10] | [JOI 92, GON 05, AZA 08] [WON 10, AZA 08] | [DON 05a, LAI 08] [LI 10a] |
| Simplify | [DHA 98, DHA 99] [LEI 09] | [BEN 04, EKI 09, OLO 98] [KUB 00, KUS 10] | |
| System level | [ANS 05, LEI 09] [MA 10, CHO 04] | | |
| Sub-system | | [HOU 06a, LEE 04, AYD 02] [AYD 04, BEN 02, BEN 04] [YAL 05, YAL 08, GOU 02] | |
| Energy parameters | [JIM 05] | [OLO 99, OLO 02, LUN 02] [LUN 04, KRE 95, ZME 02] | |
| Energy index | [LAM 10, GHI 06] | [YAL 06, YAL 07] | |
| Data pre-/post-processing | [CHO 04, NEW 10] | [KAJ 96, KAJ 97, KRE 94] [YAN 05, KAR 06, KUS 10] | [LI 10c, LV 10] [ZHA 09, LI 10b] |

**Table 1.1.** *Brief review of commonly used methods for the prediction of building energy consumption*

The engineering model shows large variations. Many considerations can be involved in developing this type of model. It can be a very elaborate, comprehensive model that is applicable for accurate calculations. In contrast, by adopting some simplifying strategies, it can become a lightweight model and is easy to develop while maintaining accuracy. A commonly accepted drawback of this detailed engineering model is that it is difficult to perform in practice due to its high complexity and the lack of input information.

The statistical model is relatively easy to develop but its major drawbacks when applied to building energy prediction are, most of the time, inaccuracy and lack of flexibility.

ANNs and SVMs are robust models at solving nonlinear problems, making them very applicable to building energy prediction. They can give highly accurate prediction as long as model selection and parameter settings are well performed. SVMs show an even more superior performance than ANNs in many cases [LI 10a]. The disadvantages of these two types of models are that they require sufficient historical performance data and are extremely complex compared to statistical models.

The comparative analysis of these commonly used models is summarized in Table 1.2. It is important to mention that this table is only a rough summary since each model has large uncertainty or variations.

| Methods | Model Complexity | Easy to use | Running speed | Inputs needed | Accuracy |
|---|---|---|---|---|---|
| Elaborate Eng. | Fairly high | No | Low | Detailed | Fairly High |
| Simplified Eng. | High | Yes | High | Simplified | High |
| Statistical | Fair | Yes | Fairly high | Historical data | Fair |
| ANNs | High | No | High | Historical data | High |
| SVMs | Fairly high | No | Low | Historical data | Fairly high |

**Table 1.2.** *Comparative analysis of commonly used methods for the prediction of building energy consumption*

## 1.7. Concluding remarks

This section has reviewed the recent work on prediction of building energy consumption. Due to the complexity of building energy behavior and the uncertainty of the influencing factors, many models were proposed for this application aiming at accurate, robust and easy-to-use prediction methods. Elaborate and simplified engineering methods, statistical methods and artificial intelligence, especially neural networks and SVMs, are widely used models. Research mainly concentrates on applying these models to new predicting problems, optimizing model parameters or input samples for better performance, simplifying the problems or model development and comparing different models under certain conditions. Each model is being developed and has its advantages and disadvantages, therefore it is difficult to say which one is better without a complete comparison under the same circumstances. However, artificial intelligence is developing rapidly, many new and more powerful technologies appearing in this field that may bring alternatives or even breakthroughs in the prediction of building energy consumption. Some of these new approach in artificial intelligence are detailed in the following chapters.