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Evaluation of spatio-temporal forecasting methods in various smart city applications

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ABSTRACT

Together with the increasing population and urbanization, cities have started to face challenges that hinder their socio-economic and sustainable development. The concept of smart cities, therefore, has emerged during the last years as a response to these problems. Advanced measurement and communication technologies enabled through smart cities have particularly played a key role in dealing with such economic, social and organizational challenges faced during the growing of cities. In this sense, using historical information provided with the mentioned technologies, various forecasting tools have been incorporated into smart city environment in order to manage more effectively its essential components such as smart grids and Intelligent Transportation Systems (ITS). For a further improvement in forecasting accuracy and hence in the management of these smart systems, recently, the information available in space has been also introduced in forecasting tools in addition to that in time. These advanced forecasting approaches, called *spatio-temporal* methods, have the capability of making use of all the available data collected from different locations. The potential benefits of these approaches have been underlined in various recent studies in the literature. In this paper, a comprehensive overview and assessment of forecasting approaches including both spatial and temporal information have been presented for the purpose of supporting the ongoing efforts for exploiting the available information in smart city applications. With this objective, the spatio-temporal forecasting methods presented in the literature are classified considering their implementation areas and model structures. Furthermore, the similarities and peculiarities of the methods classified are examined in detail, resulted in the compiling of valuable reference information for future studies on improving these approaches.

1. Introduction

A gradual increase has been occurring in the amount of people living in urban areas at the last decades due to various opportunities of large cities including better jobs with higher salaries, better education particularly at university level, wider social environments and higher living standards. According to the latest United Nations report, the population in urban areas, which is about 4 billion today, is expected to surpass 6.5 billion by 2050, resulting an increase of 12% in the proportion living in urban areas [1]. The increasing of the population and urbanization in metropolises and even growing cities, therefore, complicates the satisfaction of the fundamental needs of the people in these regions, such as housing, utilities (water, electricity and gas), medical care, welfare, education and employment.

In order to deal with such economic, social and organizational challenges to be faced during the growing of cities, a wide range of studies and projects has been presented during the last decades. These investigations have particularly focused on the applications of various smart systems in cities for the purpose of alleviating the impacts of the mentioned problems. For a specific example, advanced measurement, communication and control technologies have significantly contributed to providing and using of clean water, electricity and gas in a more effective way. Furthermore, the applications on Intelligent Transportation Systems (ITS) have decreased the time wasted in traffic and thereby reduced the corresponding carbon emissions. Besides, the efficiency of electric power systems has been increased and the integration of renewable energy sources to these systems has been facilitated, together with the studies on smart grids. The comfort level of households in residential houses has been also considerably improved thanks to the advancement in smart home technology. All these smart systems and more have reached their targets to some extent and contributed to more livable environments providing also many new opportunities to people in order to meet their requirements in an easier and quicker way. For the purpose of further exploiting the superior features of the smart systems in a feasible and sustainable way, all these independent smart systems need to be integrated in the context of a

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comprehensive framework.

With this objective, the concept of Smart City has been envisioned in the last years. A smart city has been generally defined as a developed urban area that uses Information and Communication Technologies (ICT), human capital and social capital in order to promote sustainable socio-economic growth and a high quality of life. Among the essential components of smart cities, forecasting is of significant importance since the efficient operation of smart systems is generally based on the knowledge about the plausible future conditions of these systems. It is well-known that high-accuracy renewable energy generation forecasts can allow further exploitation of renewable sources and electric load demand forecasts help the energy generation and consumption balance maintain at a minimum cost in electrical grids. More accurate forecasts both on supply side (solar and wind power) and demand side (electric load) can help power system operations and are particularly of great importance for smart grid technologies, such as Distributed Generation (DG) and Demand Response [2,3]. Besides, the forecasts of various traffic characteristics such as traffic flow and speed can minimize the effects of congestion, delay, security and environmental problems on the transportation network by using this information in intelligent traffic management. Furthermore, the forecasts of traffic characteristics might contribute to the smart energy management within smart cities as the relevant results can be utilized for better managing of the charging operations of (EVs) and even in the use of EVs as mobile storage units via Vehicle-to-Grid (V2G) technologies.

Considering the benefits of forecasts for the mentioned areas, a large number of studies on the development and application of forecasting approaches has been presented in the literature. These studies generally adopt two kinds of modelling approaches: (i) physical models that consider the mathematical description of the physical processes for the forecasts of the related variable, and (ii) statistical models that take historical data into account in order to estimate the future values. The latter approach is generally more effective in modelling the time-varying conditions in short terms and therefore provides better forecasting results up to one or two days. It can be therefore indicated that statistical approaches are more appropriate for the dynamic management of smart systems.

The statistical approaches have generally achieved reasonable forecasting results in the literature using different models such as Autoregressive (AR)-based models and machine learning methods. In order to increase the accuracy of forecasts, particularly for the longer prediction horizons, combined or hybrid models that integrate two or more models with a forecasting model for the purpose of a higher accuracy have shown significant achievement in the last decades. Taking advantage of different models can generally enable to accomplish a higher forecasting performance compared to that of single models. It can be indicated that these models can reach the possible highest accuracy level with the existing input data set; however, for a further improvement in forecasting accuracy, it is obvious that new input data are required to be included in the models. With this objective, the models that exploit all the available time series data from different locations have gained increasing interest in the last decade. The advanced measurement and communication tools, which have been recently available widely thanks to smart cities, have also contributed to development of these models by enabling the procurement and transferring of detailed data from different sources in a wide area.

These methods, called *spatio-temporal* models, combine two different forecasting approaches: (i) temporal modelling in which the expected future values are forecasted using the historical data from exactly same point, and (ii) spatial modelling in which the data are imputed at sites where no information is available. These models, therefore, consider the spatio-temporal interdependence structure in an area of interest instead of focusing on the data from only one point. The underlying idea behind these models is that the effects of a phenomenon at a given point in a system (meteorological system, traffic system, etc.) might propagate to nearby locations during a certain period due to the inertia of these systems. In other words, any information from a different location has a potential to contribute to the modelling of a target variable at a certain point. In general it is considered in the concept of these models that the data highly-correlated with the target variable will have a favorable impact on forecasting accuracy. The studies in the literature of spatio-temporal forecasting are, therefore, mostly focused on the determination of the most informative input data among a set of candidate variables from a variety of measurement sites. In addition to an improvement in forecasting accuracy, this selection process also decreases the computational times caused by such excessive data.

In this paper, the spatio-temporal forecasting methods that can be used in a smart city context are investigated in terms of their model structures, main features and peculiarities. For the purpose of examining the applications of these methods in detail, the methods are classified regarding the type of variable to be forecasted using these methods. Spatio-temporal forecasting methods are classified into three classes in this study; the forecasting approaches for renewable energy generations, for load demands and for traffic characteristics, regarding their application fields and each class is separately evaluated in different sections. Section 2 includes the studies that deal with the renewable energy forecasts, namely, wind forecasts and solar forecasts. Section 3 examines the effectiveness of spatio-temporal load demand forecasts. The implementations of traffic characteristics forecasts based on both spatial and temporal data are elucidated within Section 4. Section 5 provides insights about the effectiveness of using spatio-temporal methods for forecasting applications and summarizes the most important remarks about these approaches. Conclusions are drawn in the last section.

2. Renewable energy forecasting approaches

Generating electricity from renewable sources has gained gradually increasing interest in the last two decades due to their environmentally friendly and cost-effective operations compared to the conventional energy sources. Together with the higher penetration of renewables, particularly wind and solar energy sources, a new uncertainty problem has appeared in power system scheduling in addition to the uncertainty comes from demand side. This problem can be considerably mitigated using the renewable power forecasts on the supply side. The forecast of renewable power on demand side, which is generally produced by residential renewable energy sources connected to distribution systems, can also enable the exploitation of the energy potential at this level and therefore provide economic benefits to producing consumers known as prosumers.

2.1. Wind speed/power forecasting approaches

A rapid growth in wind energy generation has been experienced in many parts of the world in the past decade. The installed wind power capacity throughout the world reached over 430 GW at the end of 2015, with an annual growth rate of almost 22% during the last decade [4]. The projections for the next 15 years show that wind energy will provide over 19% of the total electricity supply in the world [4]. The integration of such a high-capacity intermittent energy resource into power systems poses various challenges in operating and managing of these systems since its energy cannot be dispatched in the traditional sense. For the purpose of maintaining power system reliability in the case of high wind power penetration levels, several preventive actions are generally taken. Among these precautions, wind power forecasts are of significant importance due to their effectiveness and cost-efficiency.

The studies in the literature of wind forecasting generally adopt two different procedures to forecast wind power: (i) indirect wind power forecasting, that is, the methods that forecast wind speed and convert the forecasted values to wind power forecasts using power curves, and (ii) direct wind power forecasting, that is, the methods that directly forecast the power output values of a wind turbine. These two procedures have different advantages and disadvantages compared to each other; however, in the case of that a wind farm is composed of different types of turbines or turbines with different hub heights, following the method explained in the first subgroup is appeared as mandatory. Wind power forecasting models do not differ fundamentally from wind speed forecasting models. In other words, almost the same model structures are used for both wind speed and power forecasts, excluding the use of power curves in speed forecasts to reach power values.

Wind speed/power forecasting models presented in the literature can be grouped and named regarding several criteria: (i) short-term forecasting models vs. long-term forecasting models in terms of the length of the forecasting horizon considered, (ii) statistical methods vs. model-based methods in terms of model structure, (iii) point forecasting models vs. probabilistic forecasting models in terms of the type of model output, (iv) single models vs. combined models in terms of the number of the models included, and (v) time-related models vs. spatio-temporal models in terms of the number of locations whose data are used as input.

With respect to first criterion, it can be indicated that the short term is defined as the period up to a few days and long-term forecasts cover the forecasts up to a few months. In the second group, the model-based methods, i.e., Numerical Weather Prediction (NWP) models, play a key role at larger lead times such as day ahead; however, as the forecasting times move closer to the shorter terms, the decreasing forecasting accuracy and increasing computational burden of model-based methods as well as the lack of intra-hour forecasts in the model-based methods render these model ineffective in these situations. In a contrast, statistical models are considered to be more competitive in short terms due to their capability of modelling the changing conditions in the atmosphere. In order to quantify the uncertainty in wind forecasts, probabilistic wind forecasting models mentioned in the third group have been gained importance in the literature compared to the point forecasting models that give a single-valued forecast at each time step. The combined models classified in the fourth group define the models integrating two or more different methods for a higher forecasting accuracy, particularly for longer terms. In the last classification of wind forecasting approaches, the main difference is that the spatio-temporal methods use data from different sites rather than only one point as in temporal models.

In the literature, there has been a spate of studies on the first four groups and detailed information about the methods in these groups can be found in recent literature review studies. Please see [5] for further explanations on and possible application areas of short- and longer-term wind forecasting methods, [5–8] for detailed information and related literature examples about the data-driven and physical methods, [9] for understanding the differences of probabilistic methods from the point forecasting methods, and [10] for the superiority and types of combined wind forecasting models. Considering the lack of information on the structure and advantages of spatio-temporal wind forecasting methods in the literature, a detailed evaluation of these methods with a comprehensive literature survey is presented in this section.

Spatio-temporal wind forecasting methods are mainly based on the fact that the wind speed at a given site can be spatially correlated with those at other sites and this relation might be exploited to improve the forecasting accuracy compared to the models using only temporal data. In other words, in addition to on-site observations used in wind forecasting traditionally, the data from closeby measurement points are also included in these models. It is assumed in these models that wind conditions of any area is significantly influenced by the upstream wind profile in the same area, depending on various factors including the distance between these sites, the geographical feature of the area such as terrain, elevation and surface roughness, the obstacles blocking the air flow such as buildings and trees, and the air parameters such as air density and flow velocity. As shown in Fig. 1 for an example, there might be a higher correlation between the time series of wind turbines 2

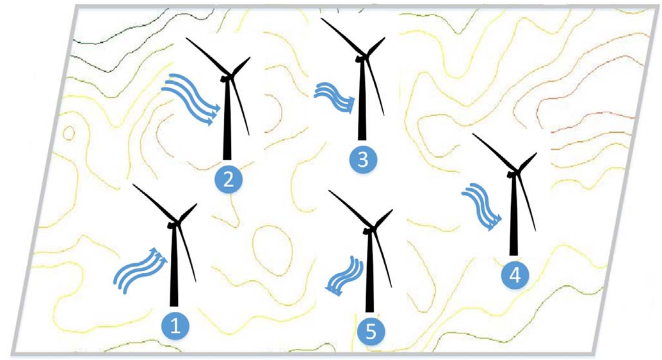

Fig. 1. An example map showing five wind turbines (or wind farms) from geographically dispersed locations. The length and direction of the arrows represent the average speed and prevailing direction of the wind over the training period, respectively in the location where the related turbine is placed.

and 4 than that of between the turbines 3 and 4 despite the shorter distance among them, due to the prevailing wind direction and relatively higher wind speed of the site where wind turbine 2 is located. The other reasons mentioned above, such as the geographical area between these wind turbines and weather conditions, also influence the level of this correlation. It can be indicated that, under stable weather conditions and a flat area, the measurements from a set of meteorological stations or wind turbines/farms distributed over a wide area, say a few 100 kilometres, can improve the forecasts for several hours ahead. In the case of a narrower area, i.e., if the data sources are closer to each other, an improvement in forecasting might be observed in a shorter look-ahead time.

The studies on spatio-temporal wind forecasting approaches were concentrated on very short-term applications at the earliest stage when the idea was put forward. As one of the earliest studies in this field, Chan et al. investigated the wind turbulence correlations for very short-time scales (from 4 min to 30 min) and short distances (up to 15 km) for the purpose of using this information in forecasting applications [11]. Alexiadis et al. proposed a short-term (10-min and 1-h) wind speed forecasting model based on Artificial Neural Network (ANN), which uses wind speeds and their derivatives from six different sites to forecast the wind speed at a certain site [12]. They subsequently applied their model to a different data set including data from a reference location and from a few upwind locations for the purpose of carrying out longer-term (up to 2 h) wind speed and power forecasts compared to the forecast time in their previous study [13]. Damousis et al. proposed a Fuzzy-based wind forecasting model using Genetic Algorithm (GA) for its parameters, which accounts for the wind speed and direction data collected in a wind park and from its neighboring sites [14]. The efficiency of the model was tested for different horizons up to 2 h ahead depending on the correlations among the available dataset. The contribution of similar wind speed data from different number of wind turbines (one to four) on the very short-term wind speed forecasts of a turbine of interest was investigated by Kusiak and Li [15]. In this study, Pearson's correlation was used for measuring the data affinity between the wind speeds from neighboring turbines and only those having similar wind speeds were included in a Neural Network (NN)-based model.

Assuming that wind speed propagates from one location to another very close location in a short time without changing too much in its current amplitude and shape due to the very similar characteristics of contiguous locations, several studies have been presented in the literature, as given above, particularly for the applications of wind turbine/farm control, load balancing and reserve operations. Together with the technological advancement in measurement and communication technologies which has enabled to collect data for a wider area, the studies on this field, particularly for longer forecasting horizons, have started to increase. These forecasting horizons are generally seen as more important in the literature since they can significantly contribute to power system operations such as economic dispatch and unit commitment. With this objective, Schlueter et al. presented a correlated echelon model relating the wind speed at a reference site and in other sites, which can be used for forecasting implementations in power systems [16]. The model was then improved by taking the direction of propagation of the meteorological event into account and using only the meteorological stations that are in the motion direction [17]. In this wind power forecasting model, the parameters were determined depending on the delays between the prediction sites and the selected reference sites. Larson and Westrick examined the use of NWP as predictor variables in addition to the on-site and off-site measurements in various forecasting models including ANN and Support Vector Machines (SVM) [18]. They concluded that both mesoscale NWP forecasts and off-site observations improve the short-term wind speed forecasting performance. Morales et al. presented an approach to generate wind scenarios by examining statistically dependent error values among wind speed of five different locations [19]. They concluded that the wind speeds at close distances are highly related; however, the magnitude of these spatial correlations is decreased for small lags in the case of larger distance between the locations. They subsequently presented a point estimate method that accounts for the spatial correlations among various wind farms with the objective of analysing a probabilistic power flow [20]. For a more cost-effective economic dispatch model compared to static dispatch and dynamic dispatch, Xie et al. presented a wind forecasting model considering short-term temporal and spatial wind power correlations [21]. Tastu et al. analysed how the spatial patterns in forecast errors evolve in space and time, and proposed three models to capture the behavior of these errors; (i) a linear model that considers the observed forecast errors, (ii) a regime-switching model that allows switching between different linear models regarding wind direction, and (iii) a conditional parametric model that accounts for the effects of wind speed on the spatio-temporal dependencies of forecast errors in the regime-switching model [22]. Ohashi and Torgo defined a regression-based wind speed forecasting method in which weighted spatial and time distances between the sites are considered [23]. Considering a power system economic dispatch problem, He et al. presented a finite-state Markov Chain (MC)-based approach in order to analyse the short-term wind generation forecasts, which accounts for spatial and temporal wind generation dynamics [24]. Dowell et al. proposed a Wiener filter for wind vector forecasts up to 6 h ahead using the spatio-temporal correlation of wind signals measured at geographically separated sites over a number of years [25]. In order to incorporate in a robust look-ahead dispatch framework, Xie et al. proposed a statistical wind generation forecast approach, namely Trigonometric Direction Diurnal (TDD) model, which considers time series collected in local and nearby wind farms [26]. Based on atmospheric dynamic principles, a similar model including geostrophic wind information, namely Trigonometric Direction Diurnal with Geostrophic Wind Information (TDDGW) model was also proposed for higher-quality forecasting results. Fan et al. presented a spatio-temporal wind speed forecasting method combining Kriging and Vector Autoregressive (VAR) models in order to use for dynamic rating of overhead lines [27]. Diehl et al. developed a visualization system for spatio-temporal pattern analysis that can be useful observing weather trends and errors in short-term weather forecasting models [28]. Assuming that there exists a low-dimensional structure managing the interactions among different weather stations and inspiring by structured-sparse recovery algorithms and Compressive Sensing (CS), a wind speed forecasting algorithm that assigns a coefficient to the data from each station proportional to their recent contribution on the forecasting accuracy was proposed in [29]. The proposed approach was subsequently combined with a Wavelet Transform (WT) model in order to decompose the wind speed data into more regular components and to forecast them individually before an aggregation process [30].

The exploitation of wind energy in power systems depends on the information about the uncertainty of wind forecasts together with forecasting accuracy to deal with the complexity of decision-making problems in these systems. These forecasts, called probabilistic forecasts, can provide the required information about the uncertainties associated with the forecasts, which is essential for effective market offering methods and stochastic unit commitment, and hence allow to analyse whether the forecasts will be lower or higher than the expected values. In other words, probabilistic forecasts quantify the uncertainty related with the conventional point forecasts and provide a distribution over forecasts instead of a single forecast, which allow to assess the reliability of forecasts and to decrease the expected balancing costs. The main interest in wind forecasting studies, therefore, has begun to focus on probabilistic approaches for spatio-temporal methods recently, similar to the case for temporal methods. In this context, Gneiting et al. proposed a regime-switching approach based on wind direction for obtaining short-term probabilistic wind speed forecasts, in which off-site predictors, i.e., geographically dispersed meteorological measurements nearby a wind farm, are considered [31]. Again in the case of that wind vector data were available for both time and space domains, they introduced two models in order to generalize their previous approach for improved forecasting performance [32]. In the first model, called TDD, wind direction was treated as a circular variable and the latter model used Cartesian wind vector at various sites for speed forecasts at a certain site. In a more recent study, Kou et al. proposed a Gaussian process model for the probabilistic wind power generation forecasts [33]. In order to enable the practical application of their model by reducing its high computational costs, they used a sparsification model based on Sample Cross Correlation Function (SCCF) of wind speed time series in nearby areas, which identifies the references sites among a set of candidate sites and extracts explanatory variables. Wytock and Kolter presented a machine-learning based wind power forecasting method that can capture temporal and spatial correlations between a collection of output variables and model non-Gaussian marginal probabilities [34]. Saunders used spatially and temporally correlated wind power generation in a Point Estimate Method (PEM) [35]. In the proposed method, it was aimed to reduce the computational cost by obtaining a set of uncorrelated random inputs with only the most prominent impacts and then by determining the PEM inputs from this set to calculate probabilistic optimal power flow results. With the objective of achieving higher-accuracy forecasts compared to those based on local information only by considering additional space-time dynamics and to reduce computational costs in a time-adaptive framework, Tastu et al. introduced a method to generate probabilistic wind power forecasts for a certain site using geographically dispersed information from its neighboring sites [36]. Both a parametric approach based on censored Gaussian distributions and a non-parametric approach based on time-adaptive quantile regression were described in this study. They subsequently presented a Gaussian copula approach for the characterisation of multivariate predictive densities describing wind power generation at different neighbor locations [37]. This approach captured the underlying space-time structure making use of the sparsity of precision matrices. Suryawanshi and Ghosh employed a probabilistic wind speed prediction approach based on a tensor decomposition method for decomposing the spatio-temporal covariance of the deseasonalized data between different locations [38]. Lastly, in addition to a parametric framework based on logit-normal distribution, a spatio-temporal model, namely, Sparse Vector Autoregressive (SVAR) model, was used within a probabilistic method in order to make the modelling of large spatial data possible [39].

Several studies investigate the use of data from the wind turbines in a wind farm to forecast the wind speed or power of a wind turbine in the same wind farm. It is assumed in these studies that the downwind wind turbines might be influenced by the wind wakes caused by the upwind turbines in a wind farm. Considering that wind farms may have different types of wind turbines (different classes, different ratings, different hub heights, etc.), these studies highlight the importance of carrying out the forecasts at the scale of individual wind turbine using the spatial dynamics in the wind farm. Moller et al. introduced an approach for time-adaptive quantile regression and evaluated its effectiveness on a large data set in a wind power plant including forecasted power production and resulting errors from Wind Power Prediction Tool (WPPT) [40]. An MC model was employed for aggregated wind generation forecasting, which considers the spatial and temporal dynamics of the power output from wind turbines in a wind farm [41]. Considering the case that a wind farm may have wind turbines with different output powers, they adopted an approach to characterize the probability distribution of total power generation. He et al. proposed a distributional forecasting approach consisting of two stages: (i) an analysis for capturing the spatial and temporal dynamics of a wind farm power generation including different types of wind turbines, and (ii) short-term wind farm power forecasting by using MC designed based on spatio-temporal analysis [42]. Croonenbroeck and Ambach made use of the spatial interactions among the turbines located in a wind park in order to carry out high-accuracy power forecasts [43]. Recently, Pourhabib et al. studied on turbine-specific wind speed forecasts, which are of importance for turbine operations such as pitch and yaw controls, in order to mitigate the unfavorable effects of these operations on turbines [44]. They presented a regime-switching forecasting approach including also wind direction and geostrophic wind as inputs, in which the set of relevant turbine sites was chosen considering the rate of change in wind speed.

Evaluating the expected wind energy for a considerable time period can provide a beneficial information for assessing the adequacy of available generation at the planning stage of a wind farm. Therefore several studies that take spatio-temporal dependencies into account have presented in the literature. As one of the first studies on this field, Haslett and Raftery introduced a model, which takes both spatial correlation and long-memory temporal dependence into account, for estimating the long-term power output of a wind turbine using speed measurements at 12 meteorological stations [45]. Karaki et al. presented a model to examine the energy resource from wind turbines at two different sites and the simulation studies showed that wind power data was dependent even in the case of that the wind speed data in the neighboring sites were weakly correlated [46]. A Bayesian approach in which data from four known stations were used as inputs was proposed in order to estimate the wind speed at a different site [47]. They decomposed the wind speed into spatial and temporal components and then modeled these components as a multivariate normal distribution and a random walk, respectively. Miranda and Dunn presented a multivariate time-series model based on wind speed spatial correlations for characterizing the resource in 20 different zones in the UK [48].

Please see [49] for some general explanations about the contribution of spatial information on wind speed and power forecasting methods, [9] for probabilistic spatio-temporal wind power generation forecasting methods and [50] for the effects of temporal-spatial dependency of wind conditions on forecasting uncertainty.

2.2. Solar irradiance/power forecasting approaches

Conversion of solar energy into electric energy can be realized by two different technologies, namely, solar thermal power plants and Photovoltaic (PV) panels. Around the world, about 35 GW of solar PV and 1.85 GW of thermal solar power were installed in 2013, taking the cumulative installed capacity to 135 GW for PVs and to 4.1 GW for thermal solar plants, respectively [51,52]. The share of solar energy in electricity generation mix in the world is expected to increase dramatically by 2030, reaching to an installed capacity of approximately 1982 GW, particularly due to the widespread use (87% of total solar power capacity by 2030) of grid connected PV panels [51,52]. The power produced by a PV panel depends generally on the available solar irradiance on the panel that varies with latitude, geographic area, position of the sun in the sky, season and atmospheric conditions. These factors significantly affect the level of solar irradiance that can be absorbed in panel in various time scales and therefore generally cause an intermittent and sporadic power generation. In order to alleviate the effects of this relatively irregular power in grids and to avoid over- and under-generation situations while still exploiting the available solar power, forecasting of the energy amount a PV system can generate in a certain time period is considered as one of the most effective solutions in terms of costs and applicability. A great deal of studies have been presented in the literature with the objective of realizing this task. In these studies, similar to the case in the first subgroup, the output power of PV panels is directly forecasted or a PV conversion model is employed for calculating the power forecasts using the forecasted irradiance values and sometimes temperature values. Two approaches are adopted for forecasting of solar irradiance in the literature: (i) using statistical methods that are based on extrapolation of historical time series data, and (ii) using satellite-based or NWP methods, which forecast irradiance values, particularly for very short terms, depending on satellite images or cloud density data.

Recently, using spatial information in temporal forecasting of solar irradiance and power has drawn increasing attention, inspiring from the significant improvements accomplished in the literature of wind forecasting. As shown in Fig. 2 for an example, correlated weather conditions such as irradiance and temperature can be observed in different locations at the same time or with a time lag. These correlations are generally based on the speed of cloud movements and distance between these locations. In the related studies, it is claimed that using the highly-correlated solar irradiance or power data from different sources allows capturing the varying weather conditions (e.g., cloud motions, daily and seasonal cycles, etc.) at different scales and hence forecast accuracy can be increased considerably.

With this objective, at the earliest stage, several approaches have been proposed for very-short term forecasts (aka nowcasting), which are of great importance for fine tuning of loads by Distribution System Operator (DSO) and within intraday electricity markets. These approaches are generally effective in terms of forecasting accuracy since clouds are generally persistent during such very short term periods. A Least Absolute Shrinkage and Selection Operator (LASSO) regression method, which is a variable selection and regularization technique for linear regression, was presented for sub-five-min solar irradiance forecasting using time series measured at a set of adjacent stations for different time lags [53]. It was concluded that the benefits of their spatio-temporal model are proportional to the number of predictors. For a similar very short term forecasting horizon, i.e, sub-5-min period, Aryaputera et al. compared different spatio-temporal kriging variants for solar irradiance forecasts and investigated the best results for a data of 13 days dominated by broken clouds [54]. A very-short term (at a

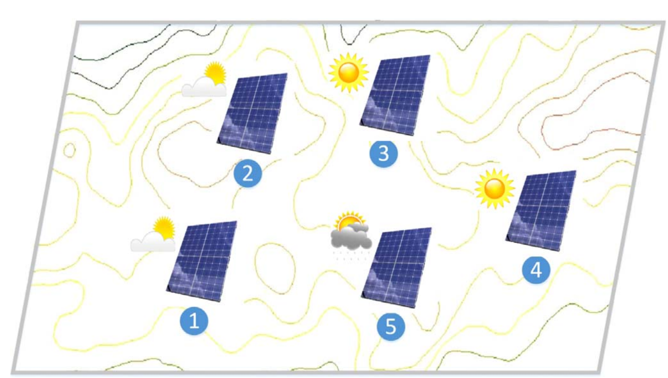

Fig. 2. An example map showing five PV panels (or PV plants) from geographically dispersed locations. The object at the upper left of each panel represents the average weather condition over the training period in the location where the related panel is placed.

temporal resolution of 15 min) statistical forecasting approach composed of two ANN ensembles was presented in [55] for three solar irradiance components, i.e., Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI), where six spinning enhanced visible and infrared imager (SEVIRI) thermal channels and data from several meteorological stations were used as inputs. A PV power output model, which uses 15-min interval measurements from a distributed PV network system consisting of 80 residential rooftop panels, was presented in [56], particularly for cloudy skies. Yang et al. presented two methods to identify a threshold distance beyond which the stations were not considered as correlated stations and thus not included in the model building [57]. Spatio-temporal solar irradiance forecasts up to 20 min were then performed in this paper implementing statistical methods such as kriging and VAR. Boland used a forecasting tool named Coupled Autoregressive and Dynamical System (CARDS) to forecast 10-min-ahead and hourly solar radiation time series for three sites [58]. The forecast errors were then analysed for cross correlation and the considerable correlations, which were observed on hourly time scale only, were taken into account for refining the forecasts. A spatio-temporal multidimensional AR method using both a large amount of satellite images and GHI measurements was employed in order to forecast GHI for a horizon from 15-min to one hour [59]. The same authors also presented a multilayer Feedforward Neural Network (FFNN) model using historical measurements from satellite-based images for GHI forecasts at the same time scales [60]. A Nonlinear Principal Components Analysis (NLPCA) was used in this study with the objective of reducing the dimensionality of spatio-temporal input data set. Yang et al. assured spatial stationary by applying a coordinate transformation and temporal stationary by detrending solar irradiance data [61]. After the transformation of data, the hourly spatial-temporal solar irradiance and PV electricity generation were forecasted using time-forward kriging method. A short-term Auto Regressive with eXternal input (ARX)-based PV power production forecasting method was presented in [62] for the purpose of exploiting spatio-temporal correlations between solar sites in the same vicinity. The contribution of the proposed model on the forecasting accuracy was evaluated for various time scales from 5-min ahead up to 2-h ahead.

Several studies have been also focused on longer-term forecasts which are of importance particularly for the integration of solar energy to power system. Zagouras et al. analysed the correlation of solar radiation time-series among satellite-derived data and ground data, and then presented various short-term (up to 3 h ahead) forecasting methods such as linear models, ANN, SVM and GA, using this correlated data [63]. A spatio-temporal method based on structured-sparse recovery algorithms and CS was presented in [64] for the forecasts of three weather variables, namely, solar irradiance, wind speed and temperature for a forecasting horizon of three hours. The forecasts were then used in a PV power conversion model for the output power of a PV system. Bessa et al. proposed a spatial-temporal method for 6-h-ahead forecasts at the levels of substation and residential PV panels [65]. The model combined two methods, namely, VAR and Gradient Boosting (GB), to examine the solar generation measurements collected by Distribution Transformer Controllers (DTC) and smart meters. A methodology combining spatial modelling and ANN was presented in [66] for local forecasting of daily GHI, which uses forecasts of four neighboring locations as inputs together with local GHI measurements. Moreno et al. compared the performance of three daily global solar irradiation forecasting methods that use irradiation data measured at 40 stations [67]. The last two models included also precipitation data and it was shown in the paper that including precipitation data improved the irradiance forecasts.

Considering the importance of uncertainty information about solar power forecasts for the operation of power system operations, a few probabilistic forecasting approach using spatio-temporal data have been presented in the literature. A short-term probabilistic forecasting algorithm based on VAR method was presented in [68] for secondary substation and residential PV levels, which explores the information from spatially distributed PV panels. Also, a probabilistic spatio-temporal forecasting framework for intra-day and day-ahead power generations was presented in [69] for both solar and wind power.

When solar irradiance measurements are sparse or unreliable in a certain location and/or for a certain timescale, synthetic data generated by various models are generally used in order to obtain a data set that can be used in forecasting tasks effectively. Spatial correlations between the data sets from different locations can also be used in generating these synthetic data with a higher accuracy. Gafurov et al. presented an approach for defining the relation between the solar radiation of two sites at different timescales and including this spatial correlation information in an algorithm for generating solar radiation time series [70].

Various explanations about the model structures of solar irradiance/power forecasting methods and some benefits of spatial information on the temporal forecasting performance can be also found in related literature surveys [71,72].

3. Load demand forecasting approaches

Knowledge of future electricity consumption for short terms ranging from minutes to several days is one of the key requirements in supplying energy to the end-user in a secure and economical way [73]. Daily operation of electric utilities including economic scheduling, unit commitment, scheduled maintenance, load dispatch, reserve management and security assessment is based on such information [74]. Using the advanced Short-Term Load Forecast (STLF) approaches in these highly capital- and technology-intensive systems, therefore, would lead to a significant improvement in both operating cost and power supply reliability [75,76].

The main strategy in load forecasting is to extrapolate the recent load behavior using generally conventional techniques over a prediction horizon. Complex and nonlinear relationship between load profile of different periods; however, causes this method to be insufficient for most applications. Besides, the state-of-the-art technologies such as smart grids and EVs make this problem more challenging. In the literature, therefore, a large number of different methods has been studied to perform the forecasts with a high efficiency considering several factors, such as prediction time, and type and amount of data.

Load forecasting methods can be grouped in different classes: (i) short-term (up to several days), middle-term (up to several months) and long-term (up to several years) forecasts in terms of time scale, (ii) appliance-level, individual household-level, transformer-level and area-level forecasts in terms of space scale, (iii) deterministic and probabilistic forecasts in terms of forecasting uncertainty, (iv) physical, statistical and hybrid approaches in terms of method and principle, and (v) temporal, spatial and spatio-temporal forecasts in terms of spatial scale.

In respect to data type, load forecasting methods based on historical data solely have shown reasonable performance especially in the last decades; however, it is well-known that the accuracy of a forecasting method may be improved to a certain level using one type of input data. Therefore much effort has been devoted recently to the load forecasting approaches accounting for the measurements from both the point of interest and the locations on its surrounding region. The underlying idea of these methods, namely spatio-temporal load forecasting models, lies in the assumption that there exists generally a significant cross-correlation among the measured data for neighboring areas and that integration of the highly correlated data from all locations to a prediction system could be used for accuracy improvement at a target location. As shown in Fig. 3 for an example, different houses (or regions consisting of multiple houses) might have similar weather characteristics and inhabitants' profile such as their income and education levels. As it is likely to indicate that there is a high correlation between these

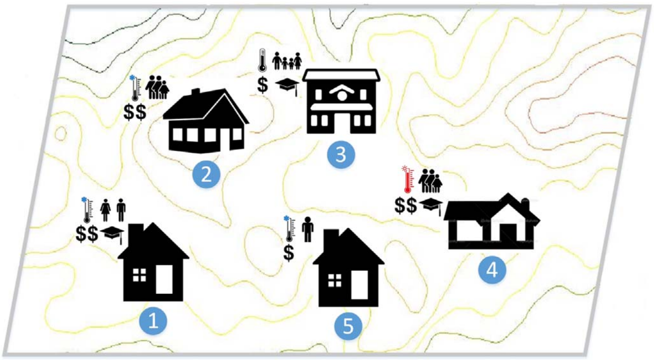

Fig. 3. An example map showing five residential houses (or aggregated load demands) from geographically dispersed locations. The objects at the upper left of each house represent the temperature of the location, occupancy of the house, and income and education levels of household.

influencing factors and load consumption profiles of houses, this information can be exploited for increasing forecasting performance.

Since the methods based on spatial information have shown promising results in the literature of renewable energy forecasting, using spatial dependencies in load forecasting has been receiving increasing acceptance in the literature. Melo et al. presented a load forecasting model that considers the distribution of approximate demand increase in a city as well as the relations between several areas of the city [77]. A modified version of this model with a reduced set of data, in which a Cellular Automata (CA) approach was used for spatio-temporal distribution of new demands, was proposed in [78]. The application of data mining and machine learning-based approaches to load forecasting has been proposed as a strong alternative to these methods. Wu and Lu introduced a method based on knowledge discovery data to examine the use of spatial dependencies of load series in load forecasting [79]. Li et al. employed a Radial Basis Function (RBF) NN for a forecast model after determining the most informative input data with a spatial correlation analysis [80]. Cong et al. combined SVM with CA for the forecasts of a highly residential area [81] and a Least Squares Support Vector Machines (LS-SVM) for spatial load forecasting of a distribution network was employed in [82]. Claiming that there generally exists a low-dimensional pattern among the data measured at different houses and that considering this fact might improve the load forecasting quality, a daily forecasting method based on sparse recovery was proposed in [83]. Useful information about the importance of data from different perspectives can be found in [84].

4. Traffic characteristics forecasting approaches

A gradual increase has been occurred in the amount of people living in urban areas at the last decades. The increasing population and urbanization in growing cities adversely influence various aspects of the quality of life. Urban traffic congestion is one of these challenging issues and therefore smart traffic management systems are seen to take its place as a key element in future smart city plans. Anticipated traffic characteristics in this context is of great importance for secure, economic and environment-friendly management of traffic. Knowing the traffic characteristics in advance can provide data support for traffic management systems and offer valuable information about traffic conditions to road users that reduces the losses in both time and fuel consumption. This information might be also useful for EV owners in optimizing the battery charging (or discharging via V2G) regarding the availability and distance of the charging stations in the route to be traveled.

Dynamic nature of traffic, however, necessitates advanced methods in order to model the interactions between the traffic level and the influencing factors. Selecting the most appropriate forecasting method mainly depends on the type of road segment such as freeway, arterial or corridor levels. Each of these levels has its own characteristics. For instance, various constraints such as signalisation (particularly adaptive signalisation) and pedestrian crossings in urban arterials make forecasting task more complex compared to freeways. Another equally important factor in choosing the model is the required forecasting interval and this period is mostly determined regarding to the application in which the forecasts are used. Generally speaking, smaller forecasting steps are seen as more valuable in practical applications due to their capability of modelling the traffic with a higher accuracy.

Conventional methods used in the forecasting of traffic characteristics provide reasonable results for only stable traffic conditions and give mostly erroneous forecasts for intense traffics caused by a large number of determinants such as large number of vehicles especially in rush hours, insufficient roads, accidents, uncoordinated signalisation and adverse weather conditions. Incorporating data from various points connected physically with each other might help forecasting approaches improve their accuracy by taking these short- and long-term changes in traffic conditions into account. Particularly, the data collected from upstream links generally have a strong effect on the forecasts of downstream links. Also the advanced technologies used for data collection enable acquiring various traffic data at a wide range of temporal and spatial resolutions. For this purpose, a detailed preliminary investigation might be carried out for a given network to find the main factors that influence the traffic characteristics and then these factors can be used as inputs in forecasting approaches. As another alternative, multi-regime models can be used for congested and non-congested conditions. However, it is generally not possible to reveal the highly complex relationship between expected and unexpected events among different traffic conditions. Furthermore, this relationship is changed over time, which makes harder to obtain a model. In order to overcome this challenging problem, forecasting approaches utilizing a large set of temporal and spatial data in a network have been introduced in the literature recently. These state-of-art models, so called spatio-temporal methods, can adapt easily to the changing conditions in traffic since they consider a large variety of information over a wide network. Therefore, a sustainable level of service can be provided for various traffic conditions including non-recurrent conditions, resulted in improved forecasts.

An example road network is shown in Fig. 4, in which the numbers represent the links with recorded traffic characteristics. In real-world implementations, it is mostly not likely to acquire high-accuracy and complete traffic data from all links due to the technical and economic considerations. Therefore, it might not be possible to use the data from exactly upstream locations for the forecasts of a given link. Instead, by using spatio-temporal algorithms, the locations which are the best candidates for a contribution to the forecasting performance can be included in forecasting tasks. It can be indicated that the links that are closer to the target link and/or that are connected physically to the target link provide the most valuable information to the short-term

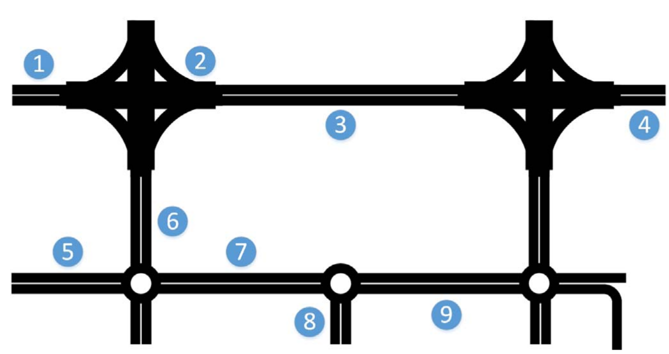

Fig. 4. An example road network map showing nine measurement devices placed at geographically dispersed locations.

traffic forecasting methods.

Among the various traffic characteristics such as flow, speed, volume, density, travel times and queue length, the forecasting of traffic flow has been identified as a key tool for reducing traffic congestion and improving transportation mobility in ITS. Particularly the short-term forecasts of traffic flow, ranging from minutes to hours, are very efficient in minimizing delays and mitigating traffic congestion by supporting proactive dynamic traffic control. There has been a wide variety of models in the area of short-term traffic flow forecasting using data in time and space domains. Since different road and traffic conditions substantially affect the model performances, these flow forecasting models can be investigated in two categories; models designed for urban networks and those for freeway networks.

As one of the first studies on spatio-temporal traffic flow forecasts in an urban network, Stathopoulos and Karlaftis applied multivariate time series models to a data set from an urban signalized arterial in [85]. In order to use in short-term traffic flow forecasts, an Autoregressive Integrated Moving Average (ARIMA) method that includes the spatial characteristics of space-time process by using weighting matrices based on the distance among the different sites was presented in [86]. Vlahogianni et al. proposed Multi-Layer Perceptron (MLP) structures using GAs in order to carry out short-term traffic flow forecasts and applied the proposed model to flow data from multiple detectors in urban signalized arterials [87]. Another spatio-temporal machine learning based approach in which the flows between neighboring links were modeled as a Bayesian network was presented in [88] for traffic flow forecasts from five min to half an hour. Similarly, Sun and Zhang examined the correlations between the link flows over a network and utilized the flow data on the correlated links only for flow forecasting at a given link [89]. A short-term flow forecasting model based on Fuzzy Rule-Based System (FRBS) combining the forecasts obtained from a Kalman Filter (KF) and an ANN, which takes spatial correlation effects into account, was presented for complex urban networks in [90] and Dimitriou et al. presented another fuzzy rule-based method for urban traffic flow predictions, using time and space-lagged data [91]. Besides, a Structural Time-Series Model (STM) was employed in [92] for short-term traffic flow forecasting using data from a number of intersections in an urban traffic network. More recently, a neurowavelet-based hourly traffic flow forecasting model was presented by Dunne and Ghosh [93]. Precipitation information, together with flow data from a high number of sites, was also used in this paper as an exogenous variable to increase the forecasting accuracy. With the objectives of handling overdispersion and smoothing nonlinear temporal and spatial variables, a spatio-temporal Negative Binomial Additive Model (NBAM) was proposed for short-term traffic flow forecasting in urban areas during different traffic conditions [94]. Another urban flow forecasting approach based on a multifactor pattern recognition method combining an ANN and Gaussian mixture model clustering was presented in [95]. Geographical information and environmental factors from adjacent roads were included in the model as input in addition to the observed variables. Most of these studies conclude that the flows from adjacent links have a greater contribution on the forecast of target link flow.

As regards to spatio-temporal traffic flow forecasting approaches presented for freeway systems, a Kohonen-enhanced ARIMA model, which includes data from upstream points as input variables, was introduced in [96] for short-term traffic flow forecasts of a motorway, as one of the earliest studies in this field. Later, the performance of nonparametric regression based on heuristic forecasting models was investigated for traffic flow forecasts in [97]. More recently, a Multivariate Normal Distribution (MND)-based model was presented in [98] to forecast supply functions and boundary variables, and these forecasts were applied to a stochastic model to include spatio-temporal traffic flow correlations in traffic state forecasts. Dong et al. presented multivariate state-space models using spatial-temporal patterns in congested and non-congested flow conditions for flow and speed forecasts [99]. Focusing on short- and long-term flow forecasts on work zones for both a signalized arterial and a freeway, Hou et al. presented different models, namely, regression tree, random forest, multilayer FFNN and nonparametric regression, using temporal and spatial traffic data [100]. Also, Li et al. proposed a set of LASSO Granger causality regression methods to determine the dependence among a huge amount of data and to filter out the irrelevant and redundant data, which leads to a flow forecasting model accomplishing a good balance between model performance and computational burden [101]. Another short-term flow forecasting method considering similar traffic patterns was employed in [102], in which the similar patterns were identified by means of a k-Nearest Neighbors (kNN) algorithm using two different metrics, namely, weighted Euclidean distance and correlation distance. All these studies come to a common interpretation that traffic flows at upstream and downstream locations have an higher effect on the forecasting performance of freeway applications.

Apart from spatio-temporal traffic flow forecasts, temporal speed forecasts using spatial information have been also investigated in a number of studies in the literature for both urban and freeway traffic conditions. With the objective of making use of irregularly spaced GPS data from multiple locations in traffic speed forecasts, Ye et al. proposed three methods, namely, naive method, modified exponential smoothing method, and modified Holt's method, and the results from these single methods were aggregated using NNs [103]. In this study, the acceleration information and information from contagious segments were also included for an improved performance. Still for urban networks, Cai et al. presented a kNN model based on spatio-temporal correlation of road segments for high-accuracy multistep speed forecasts [104]. As to implementations on freeway systems, Tselentis et al. investigated the performance of statistical and Bayesian model combination techniques for short-term speed forecasts compared to single time series models, considering also spatio-temporal traffic evolution and exogenous variables such as weather conditions and volume [105]. Furthermore, an approach based on surrogate modelling was presented in [106] for the forecasts of freeway travel speeds in a univariate (only speed) as well as multivariate (volume and speed from different locations) framework for the purpose of reducing the computational time.

As an important indication on traffic conditions, particularly for travellers, forecasting of travel time has been examined in a few studies. Hofleitner et al. presented a hybrid statistical approach based on arterial traffic flow for predicting the probability distribution of travel times by using GPS data collected from 500 vehicles that report their locations minutely [107]. For an implementation on a freeway network, Zou et al. used temporal and spatial correlations for travel time forecasts, also including diurnal patterns [108].

In addition to traffic flow, speed and travel times, Vlahogianni et al. proposed genetically-optimized feedforward MLPs for more accurate one-step volume forecasts using volume data from various locations of an urban signalized arterial [109]. Similarly, Zhu et al. presented a model based on RBF neural network for short-term traffic volume forecasts, which accounts for the flows of the contiguous intersections for improved forecasts [110]. Zhang et al. presented a model based on FRBS and GAs for multiple-horizon traffic congestion forecasts using a large number of upstream, centre and downstream traffic measurements in a freeway [111].

Also, several studies focus on developing spatio-temporal forecasting methods that can be used for different traffic characteristics. A short-term (up to one hour with 5-min intervals) speed and volume forecasting method was proposed in [112] that improves the forecasts by separating noise from systematic forecasting error. Considering spatio-temporal correlations via exogenous terms as well as multi-seasonality and non-stationarity in an urban network, a Time Space Threshold Vector Error Correction (TS-TVEC) method was presented for hourly forecasts of different traffic states such as volume, speed and occupancy [113]. Useful information about the importance and usage of spatial information in forecasting of different traffic characteristics can be found in [114].

Table 1
Classification of spatio-temporal forecasting methods based on their application areas and relevant literature.

Spatio-temporal forecasting methods	Relevant literature
Wind Speed/Power Forecasting Methods	[11–48]
Solar Irradiance/Power Forecasting Methods	[53–70]
Load Demand Forecasting Methods	[77–83]
Traffic Characteristics Forecasting Methods	[85–113]

5. Discussion and prospects

Considering the favorable results presented in the literature of spatio-temporal forecasting approaches, these approaches are investigated in this study for different variables used within a component of smart city concept. The approaches are classified considering their application areas. The related literature studies belonging to each application area are gathered in Table 1 for a concise summary of this classification.

The first part in the classification of literature examples is devoted to the studies on spatio-temporal wind forecasting. It is expected in these studies that future values of wind speed at a certain site depend on the wind speeds at neighboring sites in addition to its recent speed values at the location of interest, due to the inertia in meteorological systems. Some conclusions about these methods can be drawn by evaluating the most important results provided in the literature. First of all it is obvious that spatial information generally contributes to the forecasting accuracy for short terms. The benefits of spatial data-based methods are generally higher when the wind patterns are consistent over large areas. Furthermore, it can be stated for very low wind speeds that using spatial data from remote locations generally provides a very limited contribution, as the dependency on remote locations is related to the speed of wind. In a nutshell, the forecasting horizon for which the spatial data might be useful depends mainly on wind speed and profile, difference in the elevation of sites, distance between sites, and terrain roughness. It can be also indicated that the benefits of spatial information are directly proportional to the amount and accuracy of available data set.

In several studies, it is pointed out that selection of most relevant sites might increase the forecasting accuracy and decrease the calculation time. The critical question here is how to determine the set of the locations having most informative data. With this objective, some studies consider only the locations within a predetermined area and especially the recent studies propose methods based generally on correlation analyses. According to the results of correlation and other analyses, a weight coefficient can be assigned to each location. These coefficients are generally based on the relative distance from the location of interest, direction of prevailing wind in the area and wind profile. It is noted that the amount of spatial data to be incorporated in forecasting models should be determined regarding the tradeoff between contributions of including more data and the resulting processing time.

It is noted that designing spatio-temporal wind forecasting models in a way that they include wind direction information, i.e., considering one or more than one dominant directions known in advance, might improve the forecasting performance, as upwind or downwind sites are generally determined by wind direction. Incorporating wind direction from different locations as input to a forecasting model might also increase the forecasting accuracy. Apart from wind direction, the use of the theoretical wind influenced by only Coriolis force and air pressure gradient force, called geostrophic wind, in wind spatio-temporal forecasting methods is pointed out as an effective way for better results. Temperature measurements and forecasts, air pressure measurements, and geographical information are the other factors whose contributions on spatio-temporal forecasts are investigated in the literature and found to be considerable. In the literature there are also a few studies examining the propagation of forecast errors of wind speed and power. This information might be also used for improving forecasting accuracy.

Both DSOs and Transmission System Operators (TSOs) also require PV power output forecasts, alongside with wind power forecasts, for the better control of power systems. PV power forecasts can be indicated as one of the most practically-applicable and cost-effective solutions for optimal management of varying PV power output, together with the other widely-used technologies such as spinning reserves, energy storage systems at different scales and DR programs. The main reasons for the fluctuations and intermittency in the power output of PV panels are nighttime and passing clouds. Modelling the routine changes caused by the relative position of sun is a relatively easier task; however, for the purpose of better evaluating the moving clouds, spatio-temporal methods that use information from the adjacent sites about the cloud movements are generally required. With these methods, it might be possible to estimate the possible shading over a certain part of PV panels due to the cloud cover, which is an important information for Maximum Power Point Tracking (MPPT) methods.

In the recent years, the high amount of irradiance and power data collected by the components of smart grid structures such as smart meter and pyranometer sensors enable to investigate the benefits of spatio-temporal forecasting methods. The studies on this topic have showed that correlated irradiance/power time series can be observed with a certain time lag among different sites in the same vicinity as slow and fast clouds propagate over this geographical area. Furthermore, similar to the methods used in wind power forecasts, various methods such as LASSO are employed to choose the optimal number and location of data sources.

Compared to wind speed/power forecasting methods, very short-term forecasts are of higher importance for PV power output forecasts. Various studies are therefore presented in the literature on sub-hourly spatio-temporal forecasting methods.

In sharp contrast to forecast of stochastic meteorological quantities, demand forecasts can be indicated as a relatively easier task since the changes in load consumption have generally physical interpretations and are hence more predictable. As can be seen from Section 3, therefore, the studies on spatio-temporal load forecasting methods are very limited. These approaches, however, might still provide higher forecasting performances relative to the models using temporal data only, particularly for residential-level load forecasts at low time resolutions. In these kinds of spatio-temporal load forecasting methods, several influencing factors such as day of the week, information about houses including its size and the number of Air Conditioners (ACs), and information about the household including their occupancy, education and income levels, can also be considered to increase the forecasting accuracy. As regards the day of the week, historical data are classified into three different groups in the literature of load forecasting: (i) weekday in which load profile is almost the same for each day, (ii) weekend in which the load profile is significantly different from the ordinary weekdays, but is similar to each other except for the houses whose inhabitants work on Saturday and, (iii) public holiday in which the load use pattern is generally stochastic. It is also noted that the contribution of utilizing the similarity of days in the load forecasts has been proven in most of the recent studies since the load profile follows cycles in various time scales, with small random variations [115–117]. It can therefore be indicated that the data from same period in the previous years for a house or region might contribute to the forecasting accuracy of spatio-temporal approaches due to the relatively consistent profile of energy usage over the consecutive years. Incorporating temperature measurements and forecasts can also contribute to forecasting performance especially for summer season as there is a significant correlation between the ambient temperature and the use of ACs.

Forecasting the evolution of traffic in a certain period is of great importance for Advanced Traffic Management System (ATMS), which allows proactive traffic management and Advanced Traveler Information System (ATIS), which provides information about travel times and assists drivers on selecting the fastest route for avoiding spending too much time in dense traffic. As there is a high correlation among the traffic characteristics obtained from neighbor locations, spatial data mostly contribute to the forecasting task. It has been shown in the literature that spatio-temporal forecasting methods outperform the conventional methods particularly for abnormal traffic patterns due to incidents, weather conditions and other similar nonrecurrent cases.

Spatio-temporal forecasting approaches have been applied to both freeways and urban areas in the literature. First it can be indicated that the applications on the forecasting of traffic state on urban roads are relatively harder since traffic information is much scarcer in these areas. Second the early morning and evening periods for weekdays are generally less predictable due to the commuters who travel to work or home. Therefore the studies focus on the forecasts of these periods (i.e., around 08:00 a.m. and 17:00 p.m.) in weekdays. Regarding the results provided in the literature, it is logical to use different types of models for weekdays and weekends (including Friday for some regions) as their traffic profile is totally different.

As explained above the spatio-temporal forecasting methods are classified in this paper considering the fields where they use. From a different perspective, the methods can also be grouped taking their model structures into account, as shown in Table 2. As seen from Table 2, a large part of the spatio-temporal forecasting models is based on AR models such as Autoregressive Moving Average (ARMA) and ARIMA. The main reasons of using AR-based models intensively in spatio-temporal approaches are their relatively simpler structures and their ability of incorporating exogenous data from different sites more easily. Probabilistic spatio-temporal forecasting models have been also presented in the literature with a gradually increasing number of studies recently as the importance of forecasting uncertainty has gained much importance together with the high penetration of renewable energy sources in electricity generation, with the wider implementation of DR programs and with the increasing of the number of vehicles in the transportation networks. The machine-learning methods such as ANN, SVM, Fuzzy Logic (FL), GA, Bayesian Network (BN), MC and kNN have been effectively applied to the spatio-temporal forecasting tasks, considering the fact that machine learning methods have a superior capability of modelling nonlinear relations among different data sets. The benefits of including spatial information in forecasting approaches have been also examined through other different methods including kriging, NWP (especially for longer terms), LASSO and CA. Apart from the studies given above, efficiency of different types of models such as Random Forest, Decision Trees, Gaussian Process Regression and Linear Regression has been tested in the literature. These models have been gathered into one group named Other Models since only one example exists for each type of model. It is noted that some studies have been classified in more than one group due to two reasons: (i) some of the studies present hybrid models which combine two or more different methods, and (ii) some studies present two or more spatio-temporal forecasting methods.

Spatio-temporal forecasting methods can be also used effectively for the forecasts of other weather variables such as pressure, air temperature, humidity and precipitation. Among these variables, temperature forecasts have a wider application area in the field of energy. These forecasts, for instance, are generally used in calculating the power output forecasts of PV systems, together with solar irradiance forecasts. Besides, daily temperature forecasts provide an important information about the energy to be consumed in residential, commercial and industrial buildings since there is a high correlation between temperature and energy consumption. Due to the regular nature of temperature in a certain area and in a certain time period, it can be indicated that temperature forecasting is a relatively easier task compared to the other meteorological variables. Therefore, reasonable forecasting results can be achieved using different methods based on data from only one location. Nevertheless, there are a few studies that assess the contribution of spatial information on the temporal forecasting accuracy. A Support Vector Regression (SVR)-based forecasting approach using various meteorological variables as input, including temperature, air pressure, relative humidity, and precipitation, measured at a number of meteorological stations in a large area, is presented for daily maximum temperature [118].

Lastly, data imputation methods, which are generally used to complete the data set when the measurements are sparse, can be improved by incorporating spatial data. Therefore, the missing data problem in renewable energy, DR and transportation applications can be solved to some extent by imputing the missed data using both temporal and spatial information.

6. Conclusions

Smart technologies have gained great attention in the last decade. Some cities have already constituted smart grid infrastructures and smart transportation systems have been started to use in some areas. In order to manage emerging smart technologies, forecasting applications can be considered as one of the most effective solutions among the others. Knowing what the conditions will be in the near future enables to take an action in advance and unexpected events can be avoided accordingly. Therefore, the forecasts represent a vital step towards building smart cities. In order for these forecasting tools to be implemented efficiently and practically, forecasting tools should have high accuracy and low computational load. A large number of studies have been therefore presented in the literature for improved forecasting

Table 2
Classification of spatio-temporal forecasting methods based on their model structures and relevant literature.

Spatio-temporal forecasting models	Relevant literature
Autoregressive-Based	[19,23,27,29,30,44,45,48,57–59,62–65,70,83,86,96,97,100,103,105,112]
Probabilistic	[11,20–22,26,31–39,46,68,69,107]
Artificial Neural Networks	[12,15,55,60,63,66,67,77,80,87,103,106,109,110]
Support Vector Machines	[23,63,81,82,106]
Fuzzy Logic	[14,79,90,91,111]
Kriging-Based	[27,45,54,57,61]
Genetic Algorithm	[87,109,111]
Bayesian Network	[47,88,105]
Markov Chain	[24,41,42]
Numerical Weather Prediction	[18,43,56]
k Nearest Neighbors	[102,104]
LASSO	[53,101]
State-Space Models	[85,99]
Cellular Automaton	[78,81]
Other Models	[16,17,23,25,40,56,67,89,92,94,97,98,100,101,113]

methods such as combined and hybrid approaches. Among these approaches, the forecasting methods incorporating both temporal and spatial data have been started to use widely recently for different types of variables, due to their high performance and the development of advanced measurement and communication technologies. These approaches are based on the fact that changes in weather variables, load demands and traffic characteristics often propagate from upstream locations to the downstream areas and/or that these variables are spatially correlated in a certain region, as they are affected by the similar physical phenomena such as weather conditions and traffic states. This study, therefore, surveys the literature on spatio-temporal forecasting approaches and the related methods are classified in terms of various aspects. Their structure, differences from the conventional temporal methods and main advantages are explained in detail referring to the remarks presented in the literature. Considering the results given in the related papers, it is concluded that incorporating spatial data, particularly by examining the benefit of each data set from different locations, generally improves the forecasting accuracy without affecting the processing times considerably. In the near future, it is expected that the use of spatio-temporal approaches will become wider in conjunction with the increasing of sensors and detectors to be placed in houses, power systems and transportation network. Therefore, it will be also possible to exploit spatial data for time series forecasting of different weather variables such as temperature, pressure, humidity, rainfall, wind direction and air pollution, and even of various incidents such as forest fire, flood, landslide, avalanche, hurricane, volcanic eruption and earthquake.

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