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Upscaling of Spatial Energy Planning, Phases, Methods, and Techniques: A Systematic Review Through Meta-analysis

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Abstract:

Integrated energy planning (IEP) plays an integral role in the promotion of energy efficiency in large-scale building stock. IEP can facilitate the evaluation of energy supply and demand in current rural and urban areas for the proper allocation of available resources. This paper presents a comprehensive review of large-scale energy planning and a systematic review of the methods employed in urban and regional integrated energy planning (UR-IEP). To this effect, 234 models from 157 published papers have been collected, classified based on their aims and methodologies, and critically subjected to meta-analysis and SWOT table. Thus, this review provides a framework of the fundamental concepts in energy model design and detailed analysis to support decision-making. Further, it provides a clear comparison of the methods and characterises them based on seven basic criteria of energy models, including purpose, methodology, analytical approach, geographical coverage, mathematical approach, time horizon, and data requirements. This framework will provide urban planners with accurate and helpful knowledge for the selection of appropriate energy planning methods based on most common-focused methods that have been introduced based on 234 models published between 1960 and 2018.

Highlights:

- This paper presents a systematic review of methods in spatial energy planning.
- The methodology is based on characterisation and comparison of various IEP methods.
- Characterization is based on: purpose, method, approach, structure, scale, duration, and inputs.
- The aim, methodology, and studied location of each method are presented.
- The IEP methods are critically subjected to meta-analysis and SWOT analysis.

Keywords: Spatial energy planning, up-down methods, bottom-up methods, energy modelling characterization, urban and regional integrated energy planning, large scale building stock, urban-rural planning, systematic review, Meta-analysis

The total number of words in this paper is 9986.

List of abbreviations:

Community Energy Planning (CEP)	Community Regularity Plan(CRP),
Community Site Plan(CSP)	community master planning(CMP)
Community Detailed Plan (CDP)	Space Heating (SH)
Genetic Algorithm (GA)	Gross National Production (GNP)
Energy Intensity (EI)	Urban and Regional Integrated Energy Planning (UR-IEP)
Integrated Energy Planning (IEP)	Domestic Hot Water (DHW)
Gross Domestic Production (GDP)	Ant Colony Optimization (ACO)

1. Introduction

Based on recent urbanisation trends, it has been predicted that the population of cities globally would increase by nearly 5 million every month until 2050[1]. Due to this exponential increase in urban population, many ecological and economic crises have emerged globally, which have negatively influenced cities, and subsequently affected the procedure of urban planning [2][3][4][5]. In 1989, Barnett stated that “urban design and planning techniques have to change because cities and suburbs are changing. What was true about cities as recent as ten years ago is true no longer, and the process of evolution goes on”[3]. Today, cities are at the core of energy-oriented plans, and regulations are being scaled up from buildings to large-scale structures. This means that urban plans at all levels are increasingly involved in the reduction of fossil fuels consumption. Creating and managing effective policies associated with these urban and regional integrated energy plans require suitable methods to guarantee their functionality in certain contexts. In recent decades, the tremendous growth of energy planning models, which vary in their features such as structures and purposes, necessitated the definition of a set of approaches, which are able to provide the required assumptions for policies and future forecasting.

An Integrated energy planning (IEP) project has been implemented in 20 communities in Germany; the model was executed through GOSOL to minimise heating demand[6]. Another project was implemented in a 35 ha city area in Iran; the IEP was executed to forecast the energy supply and demand based on a zero-energy future[7]. Another IEP has been prepared for Antigua and Barbuda in 2013. The plan is written in national scale and is focused on priorities of energy strategies and financing the goals toward a sustainable renewable energy based future[8]. Energy supply in urban residential environments has been studied in 5 areas which are as lighting, communication electrical appliances, space heating, and cooling in private households and public buildings. It is noteworthy that Energy Storage System(ESS), in parallel with IEP, investigates responsive capacities of power supply and are mostly used in large-scale applications such as power generation, distribution and transmission networks, distributed energy resources, renewable energy, and local industrial and commercial facilities[9], however, this paper is specifically focused on IEP methods (Figure 1).

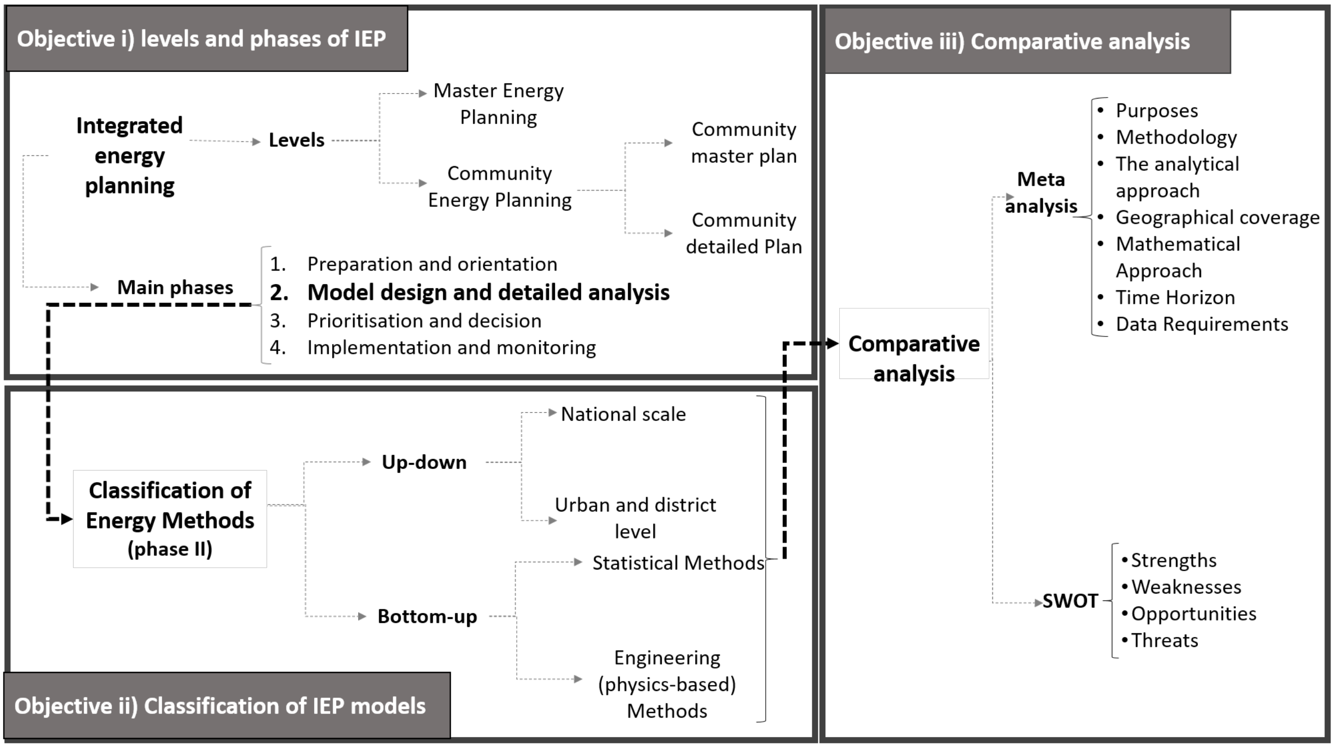

Figure 1: Structure of the IEP review

According to Mirakyam and Guio, IEP methodology has been divided into 4 phases[10] and in every phase, different functions and tasks are expected. These phases are as follows: phase I: preparation and orientation, phase II: model design and detailed analysis, phase III: prioritisation and decision, and phase IV: implementation and monitoring. In phase I, the first step towards energy planning is preparation and orientation[11]. In this step, the total conditions are analysed, and the serious issues in the planning processes are recognised; moreover, some potential solutions may be mentioned. Phase II involves analyses and planning mostly through quantitative methods and models[12]. The prioritisation and decision phase (phase III) employs scenarios to set goals and objectives for the strategies for implementing the visions, the big picture, created in step I. The last step is allocated to creating policies and action plans and the formation of a monitoring framework[10]. What is considered as "energy modelling" or "energy system modelling" is related to phase II[12], where the quantitative methods and tools are employed to analyse and forecast the demand and supply. These methods have a wide variety of toolboxes, simulations, optimisations, and even econometrics.
To date, however, energy concepts lack a comprehensive framework to help energy planners adopt the best methods when performing urban and regional planning. The main aim of this study is to propose an inclusive definition of urban plans and develop a decision support guideline with which the selection of appropriate energy plans, method, and models is facilitated. Therefore, the research questions raised by this paper are as follows. In phase II of IEP, which method is most suited to a certain purpose or situation? How have existing energy models been utilised in performing IEP in different countries?

1.1. Structure of the paper

This paper is based on a systematic review of existing energy models in phase II of IEP methods. As Figure 1 shows the main structure of this review, objectives of this study are (i) to elaborate on the main points of IEP at different levels and phases, (ii) to classify the models into different methods based on their purposes and methodologies, (iii) to perform a meta-analysis of the methods based on 7 major characteristics: purpose, structure, analytical approach, geographical coverage, sectoral coverage, time horizon, and data requirements. Next section will be focused on the first objective and will elaborate on the main points of energy planning and the process of its integration in master planning. In Section 4, will go through the second objective and in this section, the employed classification technique and the most employed methods and approaches in energy planning in multi-scales are summarised. The last part will take care of the third objective and provide a critical point of view by introducing the results of the meta-analysis of the main methods and examining their advantages and disadvantages. The adopted methodology specifically attempts to examine the IEP models from an urban planning standpoint for those who are not experts in energy, but are involved in energy subjects for planning sustainable cities, and want to clearly understand all the existing methods and tools in small and large scales.
It is worth mentioning that the main motivation for authoring this paper was to present a clear guideline for architects and urban planners; thus, energy models are analysed in a completely understandable manner, and mathematical aspects are mostly simplified in the urban context.

2. Methodology

IEP modelling relies on several variables, such as the purpose of the model, structure, input requirements, analytical approach, and the coverage scale. This paper presents a systematic review of the urban and regional integrated energy planning (UR-IEP) process and meta-analysis of the existing models which were employed mostly during the last decades. To this effect, an overall 234 observations are examined from 157 published papers released from 1960 to 2018. The first step is a literature search. In this step, papers are recognised through the keywords, energy/urban/building/models/spatial/planning, in Scopus and Web of science databases; additionally, for complete consideration, the papers, which have been referenced and cited, are considered to account for not only backward-research but also forward-research cases. In the next step, the inclusion criteria are provided; papers that contained these keywords but that were not able to cover a clearly defined methodology have not been considered in the meta-analysis. The meta-analysis is performed using RevMan (version 5.3). The characteristics have been grouped into 7 variables based on analysis, structures, and input requirements.

3. Integrating energy planning in Master planning

In 2009, the UN-Habitat published a report in which the definition of urban planning was clarified: "*Urban planning is used loosely to refer to intentional interventions in the urban development process, usually by the local government. The term "planning" thus subsumes a variety of mechanisms that are in fact quite distinct: regulation, collective choice, organizational design, market correction, citizen participation, and public sector action*"[13].
Notably, this report explains urban planning as being a difficult task (or almost impossible). The reason is that there is a wide variety of roles, forms, and perceptions in the scale of time and location. Besides, the combination of the vast topic of energy planning in this definition has made it even more complex. To date, there is no common ground on what energy planning accurately must represent. Thus far, scholars have made several attempts to achieve an integrated definition due to the wide variety of applications, but they have mostly failed. Multi-scale standpoints are employed to address the complicated aspects of this challenge; consequently, the next section will examine the three of most common focused features of energy planning on large scales in recent studies according to Krog and Sperling[14], these features are: the allied foresight, integration process, and connection of strategic aspects in large scales and operational levels.

3.1. Criteria of large-scale integrated energy planning

- **Allied Foresight:** In master plans, main strategies are formulated based on a specific vision; however, when an energy-oriented future is considered, there, definitely, must be an allied foresight to ensure every aspect of the zero-fossil fuel vision and the vision of the master plan are covered as well. Furthermore, the vision must be adapted to the aims of higher levels, such as national plans, or with parallel programs such as climate-mitigating or environmental programs [15].

- **Unified energy and planning schemes:** After aligning the perceptions and visions, the next step is to understand where and how the energy aspects must be integrated into the plan. Furthermore, it is crucial to make decisions technically and economically on all sections, including feasibility studies and land use plans or in the energy calculations tools. This process highly requires an easily understandable procedure or process map for any presentation. Notably, the performance of the abovementioned factors is not feasible without involving energy into every step, from the cognitive stages to brainstorming and decision making stages to operational levels in a certain area [16].

- **Bonded strategic and operational stages:** The energy strategies have to be included in an operational program, to be applicable in the cities. The long-term strategies must go through administrative processes to afford short-term and mid-term strategies. Afterward, instruments at various spatial scales link the main strategies to the short-time ones [16].

3.2. Community Energy Planning (CEP)

The community-scale in energy planning plays a key role since it links buildings to the city context. Community planning is the convergence point in energy planning, in which long-term strategies can be converted into mid-term and short-term tasks and policies. For integrative energy solutions, a community energy plan must focus on 5 tasks [17]:

- Identifying the end-user of energy
- Taking advantage of every opportunity to conserve energy
- Seeking renewable energy potentials
- Setting energy aims and objectives for every specific community
- Understanding the community priorities and recognising required resources

To consider a scale in-between the city and buildings, a community will be employed to convey the role of “a group of buildings”. In general, a “community” refers to a non-specific-sized social group that occupies a certain locality. In this paper, however, a “community” refers to the small-scale area (approximately 10 km^2), in which mixed-use of lands occurs [18].

Seven main steps are applicable to the energy planning process of every community [16]:

1. Recognising a private or governmental operator who is an expert in energy planning to assume responsibilities in the planning process.
2. Publishing the community vision and aims
3. Identifying an energy baseline for the community
4. Recognising all the possibilities of energy efficiency application in the community
5. Considering the economic development feasibilities
6. Identifying the service requirements in all socio-economic aspects
7. Implementing the planned short-term policies.

Community Energy Planning has been examined completely in the three parts of master planning, detailed planning, and architectural design by Huang et al. [18]. Thus, in this section, only the energy integration process into the master plan and detailed planning will be discussed.

3.2.1. Community Master Plan

The smallest spatial scale in the planning process is the community master planning(CMP) in which the main idea for a community usually is shaped, and based on it, planning visions are integrated into the energy visions. CMPs have a bottom-up statistical approach toward issues; this means it considers the neighbourhood as a system and does not enter the details of urban spaces and buildings. This approach helps urban planners to align the aims of the higher-level plans. Subsequently, objectives and main long-term strategies are provided; the last step involves collecting cognition data for the neighbourhood for preparing plans in operational levels and mostly place-demand policies.

3.2.2. Community Detailed Plan

Before developing the architectural energy design, Community Detailed Plan (CDP) plays a key role in integrating community master plan and architectural design rules. Therefore, the community detailed plan has both bottom-up statistical and engineering approach. The first one is applied as the Community Regularity Plan(CRP), and the second one is considered the Community Site Plan(CSP)[18].

Table 1 illustrates the detailed characteristics of CMP and CDP. As has been explained, CMP and CRP are applicable in a community scale and will lead to action and monitoring plans. One specific feature that distinct CMP and CRP is the period scales, while CMP must be focused on long term policies, strategies in CRP are implacable in short periods. Ultimately, CSP as the last step of community energy planning, proceed the plans through engineering approaches and simulations, the outcome of CSP is the impact analysis and energy estimations.

Table 1: community urban plans procedures

COMMUNITY ENERGY SUB-PLANS		Applicable scale	Methodology	Strategies and Policies	Time scales for policies	Outcome
Community Master Plan(CSP)		The whole area	Bottom-up statistical approach	Aims, analyzing econometric and technological data, preparing the actions plan and monitoring plans	Long-Term policies	Policies and principles
Community Ddetailed Plan(CDP)	Community Regulatory Plan(CRP)	The whole area and land parcels	Bottom-up statistical approach	Linking the goals and strategies to land parcels	Mid-term Policies and Short-term action plans	Energy intensity, Renewable energy per cent, investment index
	Community Site Plan(CSP)		Bottom-up Engineering approach	Energy consumption and generation balance Technical models with detailed simulation and accurate data		Evaluation of the effects of new technologies in energy consumption and decentralization of energy stations

4. IEP methods in large scales

The transition towards integrated energy planning requires developing methods to provide a clear vision as the prerequisite for making strategies. As has been specified, the focus of this paper is mainly on phase II of the IEP. After reviewing the main features, steps, and requirements of IEP, this section will go deeply into IEP methods. In section 4.1 the employed technique for classification of methods and the reasons for this approach. IEP methods are reviewed in two main groups, up-down and bottom-up methods which were employed extensively in the decades past to address the requirements of the next phases in the IEP process.

4.1. Techniques for classification

Thus far, a wide range of energy models has been introduced in various fields and due to the advancements in computer software, the creation of innovative and advanced models have been enhanced in the past years. This trend made it even more complicated to characterise and classify models in a solid and accurate framework. In fact, there are only a few models –if any– that fit into one distinct category. To date, several methods have been adopted to overcome this issue, such as static versus dynamic, univariate versus multivariate, and techniques ranging from time series to hybrid models; however, this paper, instead of classifying models based on one feature, characterises models based on specific characteristics that are common to all the models. In this section, a parallel system of classification has been adopted to divide the models both in horizontal for spatial scale division and vertical for the level of data input. Thus, the classification commences with splitting the approaches in two, up-down and bottom-up methods; subsequently, the approaches in different spatial scales for every method are examined. Every model in this classification has been examined based on aim and methodology; eventually, meta-analysis of the presented models through a SWOT table and the description of the variation of 7 characteristics, including the purpose, methodology, analytical approach, geographical coverage, mathematical approach, time horizon, and data requirements, are presented.

4.2. Up-down methods

Up-down methods are referred to methods that consider the historical energy consumption and estimate the energy demand, based on the input variables. Totally the developing and employing of these approaches expanded with the energy crisis in the 1970s. In these methods, buildings are not in the centre of planning, in fact, a large area containing a group of buildings is considered as an energy sink. Up-down methods are usually employed when the main aim is taking advantage of aggregated input data, which is usually available and easy to access. Generally, the up-down methods are mostly known in large spatial scaled areas such as national scale or city scale, but it should not be wrongly restricted to this. Even on a community scale, these methods could be employed for better clarification of the energy state of the neighbourhood.

The next section includes the definitions from an urban planning point of view of the most well-known models which are employed in various countries. More specific details about their methodology structures are accumulated in Table 16 in section 5.

4.2.1. National scale

In this paper, models in the national scale are presented in 11 categories. In decades past, each category has been employed in various countries with a wide variety of functions.

4.2.1.1. Econometric models

Econometric models (Table 2) are based on some forecasting, exploring, and backcasting techniques that employ historical data to signify the economic criteria of any change in different fields. In energy modelling, econometric models correlate the energy with economic variables based on historical data through linear programming.

Table 2: Summary of econometric models in energy planning

Model developed by	The main aim of the model	Methodology	Country
Samouilidis and itropoulos [19]	Examination of energy and economic growth	Developing the econometric models for industrialized countries	India
Arsenault et al. [20]	Sectorwise prediction of total energy demand	Employing Ordinary Least Square technique (OLS)	Canada, Quebec
Christodoulaki et al. [21]	Prediction of the energy requirement and CO2 emission	Deriving sector wise equations for economic activities and for every sort of energy	Greece
Sharma et al. [22]	Analysis of the requirement of three major forms of commercial energy	Employing sector wise/product wise econometric demand models by regression method	India, state of Kerala
Lu and Ma [23]	Determination of the energy consumption in industrial, transportation, residential and commercial	Using the consumption of fuel in a sector taking the case of a well off society	China
EDM (Energy Demand Model) by Gori and Takanen [24]	Development of the long term electricity consumption patterns	Using cointegration and stationary time series models	Italy
Hunt and Ninomiya[25]	Determination of the long-run price elasticity and income elasticity	Exploring the relationship between energy demand, Gross National Product (GNP) and real energy price	Japan
Raghuvanshi et al. [26]	Determination of the characteristics of the drivers of energy development	Decomposing of primary energy consumption as a product of three variables, population, per capita Gross Domestic Product (GDP) and energy intensity of GDP	India
Saddler et al. [27]	The anticipation of future energy consumption (the year 2040)	Examining the balances between different sector's energy usage	Australia
Fan et al. [28]	Analysis of the changes in energy price elasticity and elasticities of substitution	Examining the effect of energy costs on energy and non-energy sectors	China
Steenhof and Fulton [29]	Analysis of energy supply and demand	Predicting three scenarios for different economic efficiency (high, low and base case) at various national and regional sectors	Asia-Pacific region

H.Sanstad et al. [30]	A “hybrid” econometric-technology forecasting approach	combining econometric and technological elements in a set of econometric models	Western US
Mirlatifi et al.[31]	Development of an algorithm to estimate the annual peak demand of small utilities and investigate the influence of econometric variables on the power demand of N. Cyprus	Utilizing historical annual databases, analysis of variance (ANOVA), and the statistical methods	N.Cyprus,
Dai et al.[32]	An assessment of the economic impacts and environmental co-benefits of large-scale development of renewable energy toward 2050	Using a dynamic Computable General Equilibrium (CGE) model	China
Wang and Li [33]	An estimation of the relationship between the carbon emissions, population, GDP per capita, electricity consumption and energy consumption	employing regression and econometric models and analysing electricity energy development scenarios	China
Tanga et al. [34]	Development of EEMD-RVFL model for Energy price forecasting to reduce time and enhance accuracy	using traditional econometric approaches or computational intelligence methods in individual prediction	China

4.2.1.2.Unit root test and cointegration models

Cointegration tests analyse feasible correlations among some time series on the long-term. Unit root tests are able to do analysis for recognising stationarity in a time series. Time series have stationarity if a rearrangement in time cannot cause a difference in the structure of the distribution; unit roots are considered one of the reasons for non-stationarity [35]. Table 3 shows the 14 most creative unit root and cointegration models that have been implemented in the last decades.

Table 3: Summary of Unit root test and cointegration models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Masih and Masih[36]	Analysis cointegration between total energy demand and level of income	Using a dynamic vector error-correction model and multivariate cointegration tests	India, Pakistan, Malaysia, Singapore, and the Philippines
Fouquet et al. [37]	Examination of the disaggregated behaviour of UK energy crisis based on the short and long run factors of fuel consumption, economic activity, and real prices	Using Cointegration analysis to determine the long-run relationships	UK
Glasure YU. [38]	Examination of the combined effects of pure money and pure government expenditure on real income and energy demand	Employing five variable vector error correction models (VECMs)	Korea
Hondroyiannis et al. [39]	Examination of the relationship between energy demand and economic growth	Employing a vector error-correction model	Greece
Galindo LM [40]	Examination of the relation between different kinds of energy and income levels	Using Johansen procedure and ratio tests	Mexico
Lee and Chang [41]	Examination of the balance between energy demand and GDP	Employing aggregate and disaggregate data of energy demand in various sorts	Taiwan
Al-Irian [42]	Analysis of the relationship between gross domestic product (GDP) and energy consumption	Employing panel cointegration and causality techniques	Six countries of the Gulf Cooperation Council (GCC)
Lise and Montfort [43]	Analysis of the cointegration between energy demand and GDP	Using the vector error correction model (ECM)	Turkey
Zhao and Wu [35]	Prediction energy import demand	Employing cointegration and vector error correction (VEC) model techniques	China
Ang JB. [44]	Examination of the relationships between energy consumption emissions and outputs	Employing cointegration and vector error-correction	France
Yuan et al. [45]	Examination of the effects of energy demand on economic growth	Employing cointegration and VEC approach at both aggregated and disaggregated levels	China
Liu Y. [46]	Analysis of the relation between energy demand and urbanization	Employing autoregressive distributed lag (ARDL) cointegration approach	China

Lin and Moubarak [47]	Estimation of the energy-saving potential by determining energy intensity under different scenarios	employing Johansen cointegration technique and scenarios analysis	China
Narayan [48]	Hypotheses linking energy consumption with economic growth	Employing cointegration and Granger causality type tests	90 countries

4.2.1.3.Time series models

Time series models are the simplest energy models which employ a collection of observations of well-organised data items gained through regulated measurements during a reliable time. Table 4 shows the history of this model globally during the last 5 decades. As can be seen, the general function is for energy demand and supply predictions. However, source wise forecasting [24] under three different frameworks (Parabolic, linear, and chaotic behaviour), electronic forecasting in different time scales of hours and weeks [49] [50] [51] [52], and technology-wise models under four categorisation (Bass, Gompertz, Logistic, and Pearl) have been also developed under the time series models.

It is noteworthy that regression can be applied to time series problems such as autoregression, but time series methods analyzed in this paper are not based on regression, since in IEP these methods have been employed in different situations, and it depends on the purpose of the forecasting. Huang et al.[18] distinguished time series from regression models in IEP based on independent variables and through analyzing the relationship between independent and dependent variables (it can include economic level, population, building area, climate, the lifestyle of residents, etc.). Regression methods have been employed in non-ordered series where a variable is dependent on values that are taken by other variables (features), so, in fact, in the prediction process, new values of features have been taken and regression calculates the value of the target output.

Table 4: Summary of time series models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Bargur and Mandel [49]	Calculation of the energy consumption and economic expansion	Employing trend analysis	Israel
Bodger [53]	calculation of the electricity demand	Employing simple logistic functions	New Zealand
Abdel-Aal and Al-Garni [54]	Analysis of monthly electric energy demand	Employing the univariate time-series analysis	Eastern Saudi Arabia
Tripathy[55]	Creation of near-optimal models for electricity peak load forecasting	Employing a time-series-based decision support system	India
Ediger and Tathdil [56]	Prediction of the initial energy demand	Employing a semi-numerical periodic model	Turkey
Hunt et al. [57]	Development of a sector-wise energy demand model	Employing time series analysis	UK
Aras and Aras [24] [58]	The anticipation of the natural gas demand	Employing a regression time-series model	Turkey
Gonzalez-Romera et al. [59]	Prediction of the electricity demand	Using the trend extraction method	Spain
Himanshu and Lester [60]	Prediction of the electricity demand	Employing time series analysis	Sri Lanka
Mabel MC and Fernandez E. [61]	Prediction of wind energy production	Employing pearl or logistic function	India
Grey- Markov Grey-Model (singular spectrum analysis) [62]	Prediction of the coal, electricity demand	Developing a rolling mechanism for crude-petroleum consumption	India

4.2.1.4.Regression models

Regression analysis is employed when the model aims at analysing several variables, where the equation has a dependent variable and one or more independent variables. A regression model, basically, identifies the linear or non-linear relation of the dependent variable (Y) to a function, the combination of independent variables (X), and unknown parameters (β)[63].

$$Y \approx f(X, \beta). \qquad (1)$$

Specifically, in spatial energy planning (Table 5), regression models have been used to calculate the demand and supply for the coal, oil, gas [22] [62], and electricity load in short-term and long-term forecast, exploration, and even back casting[64] [65] [66] [67].

Table 5: Summary of Regression models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Jannuzzi and Schipper [68]	Calculation of the electrical energy consumption for the residential sector	Analyzing the electricity consumption classes and end-uses	Brazil
Harris and Lon-Mu [69]	Examination of the dynamic links between electricity demand and weather, presented price, and income level	using 30 years data series	South East USA
Egelioglu and Mohamad [70]	Examination of the influence of economic variables on the annual electricity consumption	Utilizing historical energy consumption, historical economic databases, and multiple regression analyses	Northern Cyprus
Yumurtaci and Asmaz [71]	calculation of the electricity demand based on the population and per capita consumption rates	Using a linear regression model	Turkey
O'Neill and Desai [72]	Examination of the accuracy in the projections of US energy consumption	Using GDP and energy intensity (EI)	US
Tunc et al. [73]	Electric energy demand	Using multiple regression analysis	Turkey
Lee and Chang [74]	Characterization of the relation between energy demand and economic growth	Examining the linear and nonlinear effect of energy demand on economic growth an inverse U-shape	Taiwan
Al-Ghandoor et al. [75]	Identification of the main drivers behind changes in electricity and fuel consumptions in the household sector	Developing two empirical models based on multivariate linear regression analysis	Jordon
Lam et al. [63]	Examination of the electricity consumption pattern in the residential and commercial sector based on principal component analysis of five major climatic variables	Using multiple regression technique.	Hong Kong
Summerfield et al. [76]	Analysis of consumption data since 1970	Developing two models by employing multiple linear regression	UK
Fumo et al. [77]	Prediction of residential energy consumption	Implementing simple and multiple linear regression and then a quadratic regression analysis	-

4.2.1.5. ARIMA models

Autoregressive integrated moving average (ARIMA) model employs autoregression analysis and moving average methods to a well-behaved time series data. ARIMA assumes that the time series is stationary or fluctuates approximately uniformly around a time-invariant mean (Table 6). Its main application is in the area of short-term predictions and it requires at least 40 historical data points. ARIMA models have been extensively used in energy demand forecasting [56].

Table 6: Summary of ARIMA models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Gonzales et al. [78]	Analysis of the energy supply and demand	Employing univariate Box-Jenkins time-series analyses (ARIMA models)	Asturias-Northern Spain
Saab et al. [79]	Prediction of Lebanon's energy demand	Employing a hybrid model is more reliable in comparison to autoregressive and ARIMA models	Lebanon
Sumer et al. [80]	Calculation of the monthly electric demand	Using three models of ARIMA, seasonal ARIMA and regression models	Balearics Islands, Spain
Ediger and Akar [81]	Prediction of fuel production	Employing regression, ARIMA, and SARIMA	Turkey

Erdogdu [82]	Analysis of short and long-run price and income fluidity of sectoral natural gas demand	Using ARIMA transfer function model	Turkey
G.boroojeni et al. [83]	Development of a multi-time-scale approach is proposed for electric power demand forecasting	The historical load is modelled as a time-series ARIMA with multiple seasonality levels and Bayesian model for evaluation	-

4.2.1.6. Input-output models

Input-output models can analyse an economic system based on the table of inputs-outputs and based on the monetary matrix. Most of the input-output models have been employed in China since 2006 (Table 7).

Table 7: Summary of Input-output models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Wei et al. [84]	Projection of China's energy requirements	Evaluating the socio-economic factors in energy usage based on six scenarios	China
Liang et al. [85]	Examination of the energy demand and emission	Developing a multi-regional input-output model for 8 regions	China
Liu et al. [86]	Examination of the indirect energy demand and the effect of energy strategies on economic factors	Developing a multi-regional input-output model with a scenario and sensitivity analysis	China
Arbex and Perobelli [87]	Analysis of the impacts of economic growth on energy consumption	Employing an integration of growth model with an input-output model	Brazil
Mu et al. [88]	Identification of dominant sectors that has a high electricity demand.	Using an input-output table of electricity demand (IOTED)	China
Alcantara et al. [89]	Examination of the electricity consumption pattern	Developing an input-output table	Spain
Zhang et al. [90]	The gain of supply-chain energy and emissions by China's building sector	Developing a hybrid input-output approach	China

4.2.1.7. Decomposition models

The decomposition models break data into its component parts. In energy planning, decompositions consist of two approaches: the first is energy consumption, by which the total production and diversion in sectoral and structural energy intensity are modelled; the second is the energy intensity approach that is able to explain the changes in sectoral and structural energy intensity, but not in total production. These models could be applied in period-wise, source-wise methods (Table 8)[91].

Table 8: Summary of Decomposition models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Ang BW [92]	Calculation of the decomposition of industrial energy demand at two levels of sector disaggregation	Using the energy intensity (EI) approach	Singapore
Ang BW [93] [94]	Analysis of the impact of structural and sectoral change on energy efficiencies	Decomposing the industrial energy consumption	Singapore and Taiwan
Sun JW [95]	Calculation of the future total energy demand and analysis of the sectoral energy intensity, structure change, and GDP	Using a decomposition model to gain separated components	15 European Union countries
Sari and Soytas [96]	Examination of the relationship between changes in national income growth and source wise energy demand and employment	Employing a generalized forecast error variance decomposition technique	Turkey
Sadorsky [97]	Examination of the effect of GDP and CO2 on renewable energy demand	Employing panel cointegration	G7 countries
Odhiambo [98]	Analysis of the relationship between energy demand and economic growth in a defined time duration	Employing the panel cointegration	Tanzania
Lean and Smyth [99]	Analysis of dispersed petroleum demand	Employing univariate and multivariate Lagrange Multiplier (LM) tests for segment integration.	US
Lee and Chien [100]	Examination of the relationship between energy demand, capital stock, and real income	Employing a Granger causality test, the generalized impulse response approach, and variance decompositions in a multivariate setting	G7 countries
Gil-Alana et al. [101]	Examination of the energy demand by the US electric power	Employing various energy sources employing segmental integration	US

Afshar and Bigdeli [102]	Prediction of Iran short-term electricity demand	Employing singular spectral analysis (SSA)	Iran

4.2.1.8. Artificial systems – Expert systems and ANN models

An expert system is an Artificial Intelligence (AI) application, which can employ any fact or rule to facilitate decision-making and problem-solving. The purpose of an artificial neural network is to recognise patterns in the data. Although these models were previously employed in electricity demand, they are currently mostly used to predict energy demand regarding macro-economic variables. Electricity price prediction and short, mid, long term load forecasting are also considered in recent researches (Table 9)[103].

Table 9: Summary of Artificial models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Aydinalp et al. [104]	Calculation of the energy consumption of appliances, lighting, and space-cooling in Canadian residential sector	Employing a neural network	Canada
Hsu and Chen [105]	Examination of the peak load planning to predict regional consumption	Using unsupervised and supervised ANN	Taiwan
Sozen et al. [106]	Presentation of two models for calculation of energy consumption: 1-population, 2-gross generation.	Employing the ANN technique	Turkey
Yalcinoz and Eminoglu [107]	Examination of the impact of variable climates for prediction of short-term load consumption	Employing ANN and historical data	Nigde, Turkey
Sozen et al. [108]	Prediction of the solar potential	Employing four models of SCG, LM, learning algorithms and a logistic sigmoid transfer function	Turkey
Benaoudaa et al. [109]	Examination of short-term electricity loads	Using ANN (employing wavelet-based non-linear decomposition) [127]	-
Gareta et al. [110]	Examination of the hourly electricity price	employing ANN	-
Pao [111]	Prediction of the electricity requirements based on national income, population, gross of domestic production, consumer price index	Employing regression, ARMA, and ANN	Taiwan
Maia et al. [112]	Prediction of electricity loads [131]	Using AR, ARIMA, and ANN	-
Ermis et al. [113]	Examination of the world green energy consumption	through artificial neural networks (ANN)	-
Sozen et al. [114]	calculation of sectoral energy consumption and greenhouse gas mitigation	Employing ANN	Turkey
Hamzacebi [115]	Estimation of the net electricity consumption on a sectoral basis	Employing ANN	Turkey
Gonzalez-Romera et al. [116] [117]	Prediction of monthly electricity demand and its fluctuation by proposing a hybrid forecasting model	Employing ANN	Spain
Azadeh et al. [118]	Prediction of Mid-term load	Employing ANN and neural network as a hybrid model	Iran
Pao [119]	Prediction of electricity consumption and petroleum	Examination of 6 linear models to present two hybrid non-linear model	Taiwan
Sözen [120]	calculation of energy needs as a model of energy dependency (ED), the first is focused on total electricity generation, gross energy consumption and the second model on sectorial energy consumption [121]	Employing two models of ANN model	Turkey
Ekonomou [122]	Examination of the long-term energy demand in a residential area	employing ANN, inputs are yearly electricity consumption and total domestic generation and power potential	Greek
García-Ascanio and Maté [123]	prediction of monthly electricity demand per hour	Employing vector autoregressive (VAR) and internal multi-layer perception model	Spain
Kankal et al. [124]	Prediction of energy consumption based on GDP, demographic data and employment and the number of exports and imports	Employing ANN and regression models with the calibration of RMSE	Turkey
Limanond et al. [125]	Prediction of the gas requirements for transportation	Employing ANN and linear regression and using by historical and demographic data and quantity of vehicles	Thailand

4.2.1.9. Grey prediction models

Grey models (GM) are based on the concepts of "lack of information" and interdisciplinary, cutting across specialised fields to fill the gap between them. Their popularity in energy fields is due to simplicity since in energy forecasting and appraisal modelling, these models can calculate the energy demand by a few data points (Table 10).

Table 10: Summary of Grey prediction models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Mu et al. [126]	Examination of the relation of biofuels consumption on rural household	Employing multivariate GM analysis	China
Yao and Chi [127]	Calculation of electricity demand	Optimizing the inputs through GM	China
Zhou et al. [128]	Prediction of the Electricity demand	Employing GM and trigonometric residual modification	China
Akay and Atak [129]	Prediction of the gross energy demand and in the industrial sector	Employing an approach of GM with rolling mechanism (GPRM)	Turkey
Lu et al. [130]	Prediction of the transportation vehicles' energy consumption	Employing GM considering the number of vehicles, vehicle kilometres of travel and GDP	Taiwan
Lu et al. [131]	Analysis of the relation between the number of vehicles, energy usage, and emission	Employing multivariate GM	Taiwan
Bianco et al. [132]	Prediction of the non-residential electricity usage	Examining GDP and cost analysis	Romani
Lee and Tong [133]	Prediction energy demand	employing grey prediction model and genetic algorithm	China
Lee and Shih [134]	Prediction of the cost of renewable energy technologies and the effects of cost on power production	Employing a multivariate GM	China
Pao and Tsai [135]	Prediction of the interrelation between pollution energy intensity and emission	Employing GM and calibration by ARIMA	Brazil
Hamzacebi and Avni Es [136]	Prediction of Electricity demand and supply until 2025	Developing Optimized Grey Modeling technique for both direct and iterative manners	Turkey
Wang et al. [137]	Investigation of the relationship between urbanization, energy consumption, and CO2 emissions	Using panel unit root tests, panel cointegration test, and panel Granger causality test	China

4.2.1.10. Metaheuristic models

As heuristic means finding by error, meta-heuristic means high-level discovery. Metaheuristic algorithm employs a certain trade-off of randomisation and local search and can operate the optimisation even with a few or imperfect input data.

- **Genetic algorithm (GA):** Genetic algorithm is a problem-solving procedure based on Darwinian evolution and natural selection. In mathematics, it starts from random models and finds more optimised solutions according to the minimisation or maximisation of a fitting function considering chromosome as a string of genes. In this model, mathematical genetics can calculate the rate of spread of a special gene. This model has been used frequently in Turkey to achieve different forecasting methods [138].
- **Fuzzy logic:** Fuzzy logic is a method for carrying out calculations based on "degrees of truth" instead of the usual "true or false". Fuzzy logic, usually, is employed in short term electric load and wind speed forecasting (Table 11)[139][140][141][142][143][144].
- **Particle swarm optimisation models (PSO):** The concept of particle swarm optimisation originates from a series of evolutionary calculation methods, which are based on flocks of birds or any other similar bio-social behaviours. Specifically, the idea is based on the fact that when birds seek food, the birds that find food emit some signals to other birds, calling them toward the food [145]. In PSO, birds are the particles, the emitted signals are positions and velocities, and the solutions act as food. Therefore, it can be interpreted that positions and velocities correlate the indicators of solutions and the speed of particles toward the solutions [146].
- **Ant Colony Optimisation (ACO):** Ant Colony Optimisation (ACO) is a paradigm for designing metaheuristic algorithms for combinatorial optimisation problems [147].

Table 11: Summary of metaheuristic models in energy planning

Metaheuristic models	Model developed by	The main aim of the model	Methodology	Studied location
Genetic algorithm	Padmakumari et al. [148]	Prediction of the long-term distribution demand	employing the Neuro-Fuzzy method	-
	Ceylan and Ozturk [149]	Examination of the coal, oil and gas demand	Employing economic indicators based on a GA model	Turkey
	Ozturk et al. [150]	Prediction of future petroleum consumption	Employing the GA specialized in Exergy	Turkey
	Ceylan et al. [151]	Examination of the transport energy demand	Employing a specialized sort of GA named – HArmony Search Transport Energy Demand Estimation (HASTEDE)	Turkey
	Cinar et al. [152]	Analysis the electricity usage, GNP, primary energy intensity, installed potential, demographic data	Employing ANN and GA	Turkey
	Forouzanfar et al. [153]	Prediction of the sectorial natural gas demand	Employing GA and non-linear programming (NPL)	Iran
Fuzzy logic	Kucukali and Baris [154]	Examination the short-term total annual electricity consumption	Employing GDP as the mere parameter and validating it by comparing the results with regression-based forecasts and MENR projections (MAED)	Turkey
	Zheng et al. [155]	development of a national saving retrofit model through Monte Carlo simulation	Employing fuzzy multiple attribute decision	China
	Liu et al.[144]	Development of a short-term forecasting model of wind power and speed	Employing fuzzy and comparing the results with Support Vector Machine (SVM) and Neural Network (NN)	Russia
PSO models	Ünler [156]	Prediction of energy demand	(PSO) based energy demand forecasting (PSOEDF) based on the indicators such as Gross domestic product (GDP), population, import and export	Turkey
	El-Telbany and El-Karmi [157]	short term forecasting of Jordon's electricity demand	Employing PSO and then using the back-propagation algorithm and autoregressive moving average method to compare the results	Jordon
	AlRashidi EL-Naggar [158]	annual peak load forecasting in electrical power systems [159] [160]	Employing PSO and then using the least error squares estimation technique for validation	Kuwaiti and Egyptian
ACO models	Toksari [161]	Prediction of the energy demand	based on separated indexes such as GDP, demography data, and import and export amounts	Turkey
	Toksari [162]	Prediction of the electrical energy demand	Employing Ant Colony Optimization	Turkey

4.2.1.11. Integrated models

Integrated energy models have a high level of information consciousness, and this means that they can consider a high level of input data dependency. In integrated energy planning, they are defined as models that are able to calculate the optimisation for a wide range of criteria, such as socioeconomic, biological, and environmental criteria.

- **Bayesian vector autoregression (BVAR) model:** Vector autoregression (VAR) is a kind of linear time-series model that can identify the joint dynamics of multivariate time series [163]. Bayesian VARs (BVARs) with macroeconomic variables were first used in forecasting by Litterman [164] and Doan et al. (Table 12) [165].
- **Support vector regression:** The support vector regression (SVR) is an efficient tool in real-value function estimation. As a supervised-learning method, SVR considers asymmetrical loss function, which can equally estimate high and low errors [166].

- **MARKAL:** The MARKAL (originated from the linkage of two words: MARKet and ALlocation) depicts both the energy supply and demand sides of the energy system. It is an analytical tool that can be adapted to model different energy systems at the national, state, and regional levels [167].
- **TIMES:** TIMES (The Integrated MARKAL–EFOM System) is a predictive and modular linear programming model based on the partial equilibrium theory; it is also an energy system cost-optimisation model (i.e. aiming to provide cheapest energy services) that minimises the sum of the annual net present value of annual costs minus revenues for the entire model time horizon [168].
- **LEAP:** The Stockholm Environment Institute in Boston developed the long-range energy alternatives planning system (LEAP) (Table 12). The tool can be employed both in bottom-up and up-down forecasting methods.

Table 12: Summary of Integrated models in energy planning

Integrated models	Model developed by	The main aim of the model	Methodology	Studied location
BVAR models	Crompton and Wu [169]	Prediction of energy demand for coal, oil, gas, hydro for 5 years	Employing Bayesian Vector Autoregression (BVAR) model	China
	Francis et al. [170]	Examination of the growth in energy consumption and relation between it and energy generation in the residential sector	Employing Bayesian Vector Autoregression (BVAR) model and Granger-causality	Caribbean countries
	Heo at al. [171]	Formulating a set of energy and carbon efficiency real retrofit decision-making situations and evaluating the role of calibration	Using the BVAR model	US
SVR models	Fan et al. and Hong [172] [173]	Prediction of the electricity consumption based on socio-economic indexes	Employing support vector model electricity load	-
	Wang et al. [174]	Prediction of the electricity consumption	Considering SVF for each of the input variables to forecast the electricity consumption	Turkey
	E.Kontokosta and Tull [175]	development of a predictive model of energy use at the building, district, and city scales	Employing linear regression, random forest, and support vector regression (SVR)	US
MARKAL models	Strachan and Kannan	Calculation of residential energy consumption to achieve a reduction in carbon emission [176] [79, 82]	Employing MARKAL	UK
	Changhong et al. [177] [178] [179]	Development of scenarios for reduction of air pollutant emission	Employing MARKAL in various decisions	China
	Chen [180]	Generation of the China's reference scenario for energy demand and carbon emission through the year 2050	Developing an integrated energy-environment-economy model	China
	Jiang et al. [88]	Analysis of the reasons for the increase in natural gas consumption	Employing MARKAL with an economic optimizer	China
	Mallah et al. [89, 90]	Presentation of scenarios to predict sectorial energy consumption patterns	Employing MARKAL	India
TIMES models	Rout et al. [168]	Calculation of long-term Sourcewise and sectorwise energy consumption and CO_2 emission	Employing TIMES G5	China
	TIMES-Canada [181]	Analysis of possible futures for the Canadian integrated energy system on a 2050 horizon	using the most advanced TIMES optimization modelling framework	Canada
LEAP models	Kadian et al. [182]	modelling the total energy consumption and associated emissions from the household sector	Employing LEAP system to analyse different policies	Delhi, India
	Kumar and Madlener [183]	evaluation of the impacts of renewable energy consumption in electricity supply systems and calculation of the CO2 emissions	developing various scenarios under the least cost approach using LEAP energy model	India

4.2.1.12. Deep learning

Deep learning methods are based on artificial neural networks that aim to identify the hierarchical in forecasting algorithm to enhance computation and increase data size due to multi-layers information processing modules. deep neural networks, deep belief networks, recurrent neural networks, and convolutional neural networks are some of deep learning models[184].

Table 13:Summary of deep learning models in energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Coelho et al.[185]	Household electricity demand forecasting mini/microgrid forecasting problem	hybrid metaheuristic model	Brazil
Kim et al.[186]	Estimation of the power consumption of individual appliances in the distribution system	Utilizing advanced deep learning and long short-term memory recurrent neural network model	South Korea
Mocanu et al.[187]	Prediction of building energy consumption	By introducing two models, Factored Conditional Restricted Boltzmann Machine and Conditional Restricted Boltzmann Machine	Netherlands
Wang et al.[188]	PV power forecasting	deep convolutional neural network	China

4.2.2. Urban and district level

To align the national level to the community scale in energy planning, up-down models must be downscaled. In this scale, the employed methods are the same as those at the national level; however, they are usually aimed at being sector-adapted to make policies more focused and accurate (Table 14).

Table 14: Summary of models in urban and district energy planning

Model developed by	The main aim of the model	Methodology	Studied location
Hirst et al. [189]	Development of an econometric model considering both technology and housing stock [190] [191]	Using econometric variables and a component for growth/contraction of the housing stock	US
Saha and Stephenson [190]	Analysis of the total energy demand	Developing a model based on space heating(SH), domestic hot water, and cooking	New Zealand
Nesbakken [192]	Analysis of the sensitivity and stability across a range of income and pricing	Two tier econometric models that examine the choice of the system (discrete) and utilization (continuous)	Norway
Bentzen and Engsted [193]	Examination of the effects of income and price on energy consumption	based on three different regression models in the residential sector	Denmark
Zhang [194]	Calculation of the unit energy consumption (UEC) for different regions based on energy demand and the demography data, and a comparison between the Chinese UEC with those of other countries	Using aggregate national residential energy values	China
Tornber and Thuvander[195]	Development of an energy model for housing stock according to real datasets	Employing the entire building register of Goteborg (68,200 buildings) and energy data from the largest energy supplier	Goteborg
Office of Integrated Analysis and Forecasting [196]	Presentation of mid-term forecasting and policy analysis based on 5 components: housing stock forecast, technology, appliance stock forecast, building shell integrity, and distributed generation equipment.	Employing the national energy modeling system (NEMS) with a current econometric energy model of the USA housing stock	US
Labandeira et al. [197]	Analysis of the residential energy demand in a source wise condition	Employing a regression model	Spain
Apartsin and Sidler[198]	Analysing ageing scenarios for prediction of power system development	Employing nonclassical volterra equations	Russia
Balaras et al. [199]	Identification of the effective energy factors that are employed for renovations	Developing an assessment for Hellenic housing stock	Greek

Siller et al. [200]	Analysis of the effects of renovating and new constructions on energy consumption and carbon emission	Developing modelling matrices which account for the renovation of buildings and new construction of buildings	Swiss
Wu and Xu[201]	prediction of energy consumption and CO2 emissions at a regional level	Employing a fuzzy multiple objective programming models	China
Fang and Lahdelma [202]	Prediction of the heat demand	Employing SARIMA combined with linear regression	Finland

4.3. Bottom-up methods

Bottom-up models employ small-scale input data and can be classified into subsets of statistical and engineering models. Totally, bottom-up models could refer to every model, provided the model is adapted to consider buildings as an independent cell of a group. The advantage of these methods is the accuracy since they are based on accurate input data of buildings. However, providing these accurate data for buildings are not as easy as providing the required input data of the up-down methods.

4.3.1.Statistical Methods

Statistical methods are based on historical information, basically. This means they utilise end-user data to calculate energy consumption. In this paper, well-documented models that have been employed in recent years are mentioned (Table 15).

- **Regression:** Regression method employs regression analysis to determine the effects of one or a group of parameters; therefore, after regressing the total energy usage into parameters, the variables with a negligible impact will be ignored to ease the calculation process [203].
- **Conditional demand analysis:** The conditional demand analysis employs regression to regress the total energy consumption onto end-use appliances. There is an advantage to this method: the required data could be simply gained through energy billings (provided the methodology proceeds some datasets such as appliance ownership), although reliable results could be achieved only when a wide variety of prerequisite data from a huge number of buildings is available [204].
- **Neural network:** A neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The function is exactly like regression models in terms of minimisation of errors; apparently, the NN models are rarely employed in modelling energy consumption. The reason might be the complexity of calculation, the prerequisite data, or even the lack of physical signs of the coefficients relating the dwelling characteristics to the total energy consumption [104].

Table 15: Summary of Statistical models in energy planning

Statistical methods	**Model developed by**	**The main aim of the model**	**Methodology**	**Studied location**
Regression	Hirst et al. [205]	Examination of the weather and non-weather sensitive elements of the household energy consumption of dwellings	Employing Princeton scorekeeping model and regressing the energy billing data onto a non-weather dependent constant	USA
	Tonn and White [206]	Analysis of occupant behaviour	Developing a regression model with four simultaneous equations	-
	Douthitt [207]	Development of a model of residential space heating fuel use	Employing regressing in consumption as a function of present and historical database	Canada
	Fung et al. [203]	Determination of the impact on Canadian residential energy consumption due to energy price, demographics, and weather and equipment characteristics	Employing a regression model	-
	Raffio et al. [208]	Assessment of the potential energy-conserving changes	Identifying energy conservation potential within a regional area	
	Torabi Moghadam et al. [209]	Estimation of the energy consumption of several residential building stocks for heating space	Employing a wide range of variables and based on a 2D/3D- Geographic Information System (GIS) and Multiple Linear Regression (MLR)	Italy

Conditional demand analysis	Parti and Parti [210]	Approximation of the occupant behaviour and determination of the use level of individual appliance	Employing CDA and regression methods	US
	Aigner et al. [211]	Estimation of energy use of appliances in each hour of the day	Employing CDA models	US
	Caves et al. [212]	Calculation of the electrical energy consumption of Los Angeles customers	Developing a CDA model of the residential	US
	Bartels and Fiebig [213]	Determination of the estimates of certain end-uses based on occupant behaviour	Proposing an alternative method based on the CDA model	-
	LaFrance and Perron [214]	determination of the changes in annual energy consumption	Employing an extended CDA method by incorporating energy consumption data	Quebec
	Hsiao et al. [215]	Identification of values which collaborate behavioural aspects better than a single EM estimation	Employing the work [216] and [217] by utilizing sub-metered end-use energy consumption	-
	Bartels and Fiebig [216]	Enhancement of ''efficiency'' of submetering of the model by Hsiao et al. [219]	Employing a review of the house appliance survey prior to the sub-metering measurement	Norway
	Aydinalp-Koksal and Ugursal [217]	Analysis of the entire energy consumption of the Canadian residential sector	Developing a national residential CDA model	Canada
Neural network	Cetin and Novoselac [218]	Analyzing the use of patterns of residential appliances and HVAC systems in single and multi-family households.	Using HEMS	US
	Issa et al. [219]	Identification of the gap between actual energy consumption and the EPI rating	Developing a NN model that uses energy performance index (EPI) and conditioned floor areas of a group of dwellings with billing data	US, Florida
	Mihalakakou et al. [220]	Development of an energy model of a house	Using the NN methodology based on atmospheric conditions	Greece
	Aydinalp et al. [221]	Development of a comprehensive national residential energy consumption model	Employing the NN methodology in three separate models: appliances, lighting, and cooling (ALC)	-
	Aydinalp et al. [222]	Analysis of socioeconomic elements	Employing the NN model and using a dataset of alternative energy sources	-

4.3.2. Engineering (physics-based) Methods

Engineering methods calculate energy consumption based on geometry, envelope fabric, equipment and appliances, climate characteristics, and indoor environment criteria. The advantage of this model is as follows: since new technologies do not have any historical data, the occupants' behaviour must be considered to obtain an accurate model, which differs considerably case by case and is completely unpredictable (Table 16).

Distributions: If the engineering models are developed based on appliance ownership and end-use distribution to forecast energy consumption, they are classified under the distribution sublet methods; even if their scales are national or regional, they will be classified under the bottom-up method due to their level of disaggregation.

Sample: Employing actual building samples can show a wide variety of housing stock and could be a good indicator for ensuring that the sample size is large enough. Since these models require huge databases, the applicability is limited.

Archetype: Archetypes, as a subset of engineering models usually employ various details to link a small group of buildings together. Archetypes modelling methodologies are based on a huge amount of details through computer-aided simulations. The advantage of this method is that due to the few number of archetypes, time efficiency can be enhanced through simulation, and the further the advancement in software, the more the applicability of these methods progresses

Table 16: Summary of engineering models in energy planning

EM Models	Model developed by	The main aim of the model	Methodology	Studied location
Distributions	Capaso et al. [223]	Calculation of the total electric demand	Developing a model for a residential sector based on population and lifestyle of residents	Italy

	Jaccard and Baille [228]	Calculation of the unit energy consumption	Employing INSTRUM-R simulation based on the costs and behavioural parameters and historical data and technological distribution	Canada
	Kadian et al. [182]	Development of an end-use energy demand model of a residential sector	Using a simplified endues consumption equation to incorporate the penetration and use factors of all households	Delhi, India
	Saidur et al. [224]	Analysis of the exergy by estimating the total appliance's variable and the dividing of the efficiency	Developing a model for non-space heat residential energy demand	Malaysia
	Wu et al. [225]	Design of an optimal retrofitting strategy for achieving maximal energy savings and maximal NPV (Net Present Value)	Developing a TBT (time-building technology) framework	
Sample	Farahbakhsh et al CREEM [226]	Calculation of the energy usage and calibration process	Developing the Canadian Residential Energy End-Use Model (CREEM) based on 16 archetypes and comparing the billing data	Canada
	Larsen and Nesbakken [227]	Development of a model for housing stock	Employing ERAD	Norway
	Ramirez et al. [228]	Computation of the hourly energy usage of buildings	Employing eQuest simulation software for a commercial region	US
	Guler et al. [229]	Analysis of the energy efficiency upgrades and GHG emissions	Employing an economic residential energy model to study	
	Swan et al. [230]	Development of a residential energy model	Employing a detailed database of nearly 17,000 houses	Canada
	Ascione et al. [231]	Presentation of the energy behaviour of the explored building stock	Developing SLABE model through Latin hypercube sampling to generate Representative Building Samples (RBSs)	Italy
	Hoos et al. [232]	Development a method to design retrofit scenarios	Employing a method of sampling for categorization of the end-energy for heat use of the public building stock	Luxembourg
Archetype	MacGregor et al. [233]	Development of a residential energy model based on the 27 archetypes	by employing hourly analysis program (HAP)	Nova Scotia
	Kohler et al. [234]	Decomposition of the big databases into details and basic building elements considering materials and operations	Developing energy, and monetary model	Germany
	Huang and Broderick [235]	Development of an engineering model for SH and cooling loads	Employing prototypes in multifamily and single-family 16 various regions	US
	Snakin [236]	Development a model to find the factors of conservation and alternatives for fuel	Employing history databases and population and buildings features	Finland
	Tornberg and Thuvander. [195]	Prediction of many details such as building fabric, glazing, ventilation, water heating, space heating, and fuel costs	Developing energy and environmental model to base on archetypes and employing GIS	UK
	Shipley et al. [237]	analysis of the impacts of building envelope improvements	Developing a monetary and energy emission model based on archetypes and ASHRAE	US
	Carlo et al. [238]	Development of a model based on archetypes for commercial-buildings	Employing some initial parameters such as building energy regression equation to be roof area ratio, facade area ratio, and internal load density	Brazil
	Shimoda et al. [239]	Identification of the insulation levels for the city scale	Developing a residential end-use energy consumption model based on archetypes	Osaka, Japan
	Wan and Yik [240]	define different window areas facing the sun	Developing archetypes based on floor plans	Hong Kong
	Palmer et al. [241]	Development of a model to calculate SH and DHW	Employing BREDEM-8 (Building Research Establishment Tool)	UK
	Nishio and Asano [242]	Identification of the distribution and housing variables	Developing a tool to generate archetypes to employing Monte-Carlo methodology	Japan
	Petersdorff et al. [243]	Developing a European building stock by considering 5 standards and 8 insulation standards	Employing Ecofys's BEAM for modelling heating demand in three different climate zones	EU
	Clarke et al. [244]	Development of a model to calculate the thermal energy demand	Employing ESP-r in the Scottish building stock	UK
	Ballarini et al. [245]	Implementation of a cost-optimal analyses	Developing a national building Typology for European building stock	Italy

Cerezo et al. [246]	Development of the visions for a model	Employing a standard input format	US
Yang et al. [247]	Estimation of the energy performance	Employing a clustering method to select representative buildings and normative model to calculate energy parameters	China

5. Comparative analysis and discussion

In Section 4, methods in phase II of IEP with related samples in different geographical locations have been provided; however, to clarify the basis on which these methods are employed in different occasions, characterisations of these methods are required. Table 17 presents the comprehensive framework of 7 basic features of methods which are employed in IEP.

SWOT analysis is an effective way that energy modelers can find out the weaknesses and strengths of the models and how the threads and opportunities can affect the requirements and outcomes of the calculation. Also, urban planners can understand compatible models that can be employed together. Thus, this SWOT table (Table 18) can be a guideline for energy modelers and urban actors to have smarter choices between potential models. Furthermore, SWOT analysis with meta-analysis together is an enhanced helpful approach for decision making because of its ability of presenting an extensive and critical comparison among models.

Table 17: characterization of the methods based on 6 criteria

	Purposes		**Methodology**	**The analytical approach**	**Geographical coverage**	**Mathematical Approach**	**Time Horizon**	**Data Requirements**
	General	**Specific**						
Econometric	Fo/Ex/Bc	De/Su/Im	ME/EEQ	UD	Na	L	Sh/Lo	Quant/Ag
Unit root test and cointegration	Fo/Ex	De/Su/Im	ME/MC	UD	Na	L	Sh/Lo	Quant/Qualit/Ag
Time series	Fo/Ex	De/Su/Ap/Im	Opt	UD	Na	L	Sh/Lo	Ag/Quant
Regression	Fo/Ex/Bc	De/Su/Ap/Im	ME/Opt	UD/BU	Na/Reg/Lo	L/NL	Sh/Lo	Ag/Disag
ARIMA	Fo/Ex	De/Su/Ap	ME/Opt	UD	Gl/Na	L	Sh/Lo	Ag/Quant/Qualit
Input-output	Fo/Ex	De/Su	ME/MC	UD	Na/Reg	L	Sh	Ag/Disag/Quant
Decomposition	Fo	De/Su/Ap	ME/Opt	UD	Na	L/NL/MI	Sh/Lo	Ag/Disag/Quant/Qualit
Grey predictions	Fo	De/Su/Ap	ME/Opt	UD	Gl/Na	L/NL	Sh/Med/Lo	Quant/Ag/Disag
ANN	Fo	De/Su/Im/Ap	ME/Opt	UD	Na/Reg/Lo	NL	Sh/Lo	Disag/Quant/Qualit
Genetic algorithm	Fo	De/Su/Ap	Opt	UD	Gl/Na/Reg/Lo	L/NL	Sh/Lo	Ag/Disag/Quant

Fuzzy logic	Fo/Ex	De/Su/Ap	Opt	UD/BU	Gl/Na	NL	Sh/Lo	Quant/Disag
PSO	Fo/Ex	De/Su/Ap	ME/Opt	UD	Na/Reg	NL/MI	Lo	Disag/Qualit
BVAR	Fo/Ex	De/Su/Ap	ME/Opt/MC	UD	Gl/Na/Reg/Lo	L/NL	Sh/Lo	Disag/Qualit
SVR	Fo/Ex	De/Su/Ap	Opt	UD	Na/Reg	L/NL	Sh/Lo	Disag/Qualit
ACO	Fo/Ex	De/Su/Ap	ME/Opt	UD	Na/Reg	NL	Lo	Disag/Qualit
MARKAL	Fo/Ex	De/Su/Im/Ap	ME/Opt/Sp	UD/BU	Na/Reg	L/D	Lo	Quant/Disag
TIMES	Fo/Ex	De/Su/Im/Ap	ME/Opt/Sp	UD/BU	Na/Reg	L/D	Sh/Lo	Quant/Disag
LEAP	Fo/Ex	De/Su/Im	De:ME Su:Simu	UD/BD	Gl/Na/Reg/Lo	L	Med/Lo	Ag/ Quant
Conditional demand analysis	Fo/Ex	De/Im	ME/Opt	BU	Reg/Lo	L/NL	Sh	Ag/Disag
Neural network	Fo	De/Su/Im/Ap	ME/Opt	BU	Na/Reg/Lo	NL	Sh/Lo	Disag
Distributions	Fo/Ex	De/Su	Opt/Simu	BU	Na/Reg/Lo	L/NL	Sh/Lo	Quant/Ag/Disag
Sample	Fo/Ex	De/Su/Im/Ap	Opt/Simu	BU	Reg/Lo	L/NL	Med/Sh	Ag/Disag
Archetype	Fo/Ex	De/Su/Im/Ap	Opt/Simu	BU	Reg/Lo	L/NL	Med/Sh	Ag/Disag/Quant/Qualit

L=linear, Fo=Forecasting, Ex=Exploring possible scenarios, Bc=Backcasting from future to current situation, De=Demand, Su=Supply, Im=Impact evaluating, Ap=Appraisal , ME= Macro Econometric, Opt=Optimization, Sim=Simulation, Sp= Spreadsheet(Toolbox) Models, UD=Up-Down, BU=Bottom-Up, Na=national, Reg=Reginal, Lo=Local, L=Linear model, NL=Non-linear model, MI=Mix Integer Model, D=Dynamic model, Sh=Short-term, Lo=Long-term, Med=Medium-term, Quant=Quantitative model, Qualit=Qualitative model, Ag=Aggregated, Disag=Disaggregated

Table 18: SWOT analysis of the three major methods in phase II of IEP

Up-down	**National/ Districts**		**Strengths**	**Weaknesses**
			• Economical and quick implementation • Typically, an acceptable accuracy (approximately ±5% [248]) • Easy to track changes in energy consumption • Identifying the effects of employed equipment • Flexibility in the prediction of all utilities (electric, gas, water, …) and non-utility cases such as production inputs • Appropriate for prediction of costs and facility performance	• The gross analysis creates unknown aberration causes
			Opportunities	**Threats**
			• In need of long-term data and Needless of collecting detailed data • Capable of handling calculation both linear and nonlinear data in socio-economic and demographic aspects	• In need of historical data to form a model but even extensive historical data cannot consider technology progresses • Incapable of output division in terms of technology, end use, etc.
Bottom-up	**Community**	**statistical**	**Strengths**	**Weaknesses**
			• Consideration of occupant behavior • The inclusion of socio-economic effects down to the level of individual building • Detecting any change in individual facility process • Extreme accuracy in modeling due to the exact data collection in small scales	• Highly dependency on historical data and forecasting future trends without consideration of technology progresses • Unresponded to multicollinearity • Disregarding the variation of end-uses by selecting surveyed samples
			Opportunities	**Threats**
			• Utilizing billing data and simple survey information	• In need of weather, billing or surveyed data
		Engineering	**Strengths**	**Weaknesses**
			• Consideration of variation in end-uses • Flexibility and accuracy in simulation through softwares • Accommodating the effects of each process employing a linear or nonlinear submodel.	• Disregarding the socio-economic aspects • In need of complicated energy modelling • Unable to generalize the model to other models
			Threats	**Opportunities**
			• Needless of historical data	• In need of detailed weather, architectural, and technological data

5.1. A meta-analysis of the spatial energy models

To sum up, a meta-analysis has been performed, meta-analysis is a statistical mechanism for analysing specific features in a series of studies. The main aim of the meta-analysis in this study is to examine the disciplines of employing various methods regarding 7 distinct variables of Table 16 in all 234 models. Through this analysis, by taking the advantages of commonly-employed methods in recent studies, the answer to the question of this study that which method most suits to a certain purpose or situation will be provided. Besides, this meta-analysis can clarify the reason for the variation in the process of employing different methods and also overriding of one method in comparison to other methods To accomplish this, energy planning models (234) related to phase II of the UR-IEP applications from 157 published paper went through this mechanism. These models have been classified based on the employed method in 23 classes. In the next step, after characterisation of the methods based on the 7 distinct variables (Table 17), RevMan (version 5.3) is employed to perform a meta-analysis to discuss the approaches that were accomplished during the last decades. The output of RevMan is summarised in table 18, with two index of mean and standard deviation. The column Mean shows the average of models that include the description of 1. For example about the porpuse of the studied models, it shows that 70% of the papers(164 models) are focused both on exploring future scenarios and forecasting, and specifically, 68% of models(159 models) are focused on demand and supply with a very low deviation that shows most of the models are concentrated on demand and supply calculations. The same happened for time horizon that RevMan recognised that 68% of the models (160 papers) are focused on short-term planning. In contrast, the number of modelling that is carried out on the local scale is few. Accompanied by only 54 bottom-up models, it is clear that this trend is not common; however, most of these models have been introduced in recent years and their number is increasing considerably.

Table 19: Results of Meta-analysis in collected variables

Variables	Description	Mean	St. deviation
Purpose			
General:	1: if it is Forecasting and exploring ; 0: otherwise	0.705	0.456
Specific:	1: if it is demand and supply; 0: otherwise	0.688	0.208
Methodology	1:if it optimization; 0:otherwise	0.511	0.415
The analytical approach	1: if it is bottom-up; 0: otherwise	0.233	0.423
Geographical coverage	1: if it is local; 0: otherwise	0.330	0.499
Mathematical Approach	1: if it is linear programming and not non-linear; 0: otherwise	0.358	0.479
Time Horizon	1: if it is short-term; 0: otherwise	0.682	0.220
Data Requirements	1:if it is quantitative and aggregated; 0:otherwise	0.426	0.461

6. Conclusion

Integrated energy planning has been increasingly highlighted due to today's energy considerations. This paper has attempted to classify existing models into IEP methods and analyse their functions; therefore, a systematic review of the models published from 1960 to 2018 has been provided. The conclusion aims at responding to the questions mentioned in the introduction section. To this effect, after a brief introduction of IEP and its phases in several levels, existing models were classified into 23 groups based on their methodologies and objectives, and seven basic features of these methods were compared in Table 17. It is noteworthy the classification of the employed methods has shown that so far some contemporary machine learning methods which already are common on individual building scale(e.g. Random forest) are not studied in IEP. The meta-analysis has shown that, although the majority of the models are focused on a national-scale up-down analytical approach, many models in IEP have recently been adapted to short-term and local scale. and if this intendancy continues in the future, the models in phase II of IEP are going to be increasingly focused on the local scale, this trend has begun relatively from 2010 due to progression of engineering software and also the convenience of providing data of individual buildings in large scales Thus, a review of the software that is employed in the calculation and simulation process of energy planning with a clear identification of their functions in every phase is essential complementary research for this review.

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