Current tendencies in the integration of renewable resources And modeling of wind energy systems

(State of the art, GIS Prospection, modeling and optimization methodologies)

[1]Bizuayehu Abebe Worke, [2]J.Antonio Dominguez Navarro

[1]CPS, Mechanical Engineering Department, Renewable Energy and Energetic Efficiency Program Student
[2]CPS, Electrical Engineering Department
University of Zaragoza,
María de Luna, 3 – 50018 Zaragoza, Spain
Tel. +34 976 762 401 Fax. +34 976 762 670 e-mail: **bzy_citd@yahoo.com**, jadona@unizar.es

ABSTRACT

This paper has as an objective of describing the current tendencies in the modelling and integration methodologies of renewable resources, specifically applied for wind resources. Presents also some of but not all the popular state of the art methodologies used in prospecting, modelling, optimizing the integration of wind renewable energy systems.

Depicts the degree of progress attained in wind resource assessment methodologies as well as the different approaches of wind energy modelling. This paper has methodological value for all who want to start working with the wind resource assessment methodologies, giving an insight about the different commonly used approaches to manage wind energy resource assessment and system integration issues.

INTRODUCTION

Why, renewable is not gaining ground now days? It seams clearly visible that the growth rate in this segment is not encouraging. There are two main reasons from optimization perspective; the first is how to survey the best RE sitting to harvest the maximum energy, with competitive unit cost and second is a robust prediction system to minimize uncertainty problems. Both issues are contrary and subject of continuous discussion and research works of the scientific world.

Therefore, the whole effort is engaged about how to improve the confidence of effective RE competitiveness. These days, it is possible with more or less uncertainty to determine the harvest time, but the amount remains still unclear? Besides to this fact, the dynamics of environmental set has put serious limitations in to it, due to stochastic nature.

This paper is intended to describe the state of the art of current wind RE prospecting, wind modeling and optimization tools applied to integrated renewable energy systems. The main objective of this paper is to depict the degree of progresses in developing methodologies for integrated renewable resources using state of art tools.

Key words: Prospection, Optimization, Integration, Model

Nomenclatures: RE –Renewable Energy, NWP-Numeric weather prediction, DSM-Demand Side Management, MCP-Measure Correlate Predict, WRA- Wind resource Assessment

1-INTEGRATION OF RENEWABLE ENERGY RESOURCES

Even the modest-scale integration of renewable energy resources at minimum integration costs requires research in three main areas:

A-RER, prospection, optimum sitting and capability assessment

B-Dynamic Renewable Energy models

C-Additional possibilities for decision flexibility

The above stated components have strategic relevance for the integration of wind energy. Here under shortly it will be discussed about currently used prospecting tools, energy prediction models, and optimization tools.

2-WIND AS A RENEWABLE RESOURCE

Wind has three major classes of origin: primary, secondary and tertiary. The primary or global origin of wind resource in a simpler form, four atmospheric forces: pressure force, Coriolis force (due to earth rotation), inertial force (due to global scale circular motion) and frictional forces (with the earth's surface) determine the global perspective of wind motion. Secondary sources of wind include hurricanes, monsoon circulation and cyclones. Thirdly, diurnal variations, thunderstorms, tornadoes etc. determine short-term, small-scale wind variations **[1].**

One of the primary goals of wind energy site assessment is the estimate of long-term wind energy at a potential site. These include the utilization of wind maps or atlases, reanalysis software's or mesoscale modelling etc. **[2]**

The ideal site assessment method should result in an overall reduction in the uncertainty of the estimate of the long-term wind resource, rapidity of the site assessment, and minimized costs even tough assessment methods yield different excellence in their exhaustiveness

3.-WIND PROSPECTION, OPTIMUM SITTING AND CAPABILITY ASSESSMENT

Wind can be measured directly by anemometers put on buoys, masts, rawinsondes and ships or indirectly by remote sensing instruments either ground located (sodar, Doppler radar and lidar) or carried on satellites (altimeter, scatterometer and synthetic aperture radar (SAR)).

A-Ground based WRA:

1-Continuous wind monitoring approach

This conventional WRA approach is based on completely stationary meteorological towers, which measure continuously at one location and therefore for the duration of their deployment, capture both short term and the seasonal variations in the wind resource. These are typically 10, 40 and 60 m tall with cup anemometers, wind vanes, thermometers, and barometers, positioned at multiple heights or using an integrated multi-measuring device and data logger incorporated on the tower. **[3]**

2-Discontinuous wind monitoring approach

One of the innovative approaches is the round robin site assessment method, which aims to increase the number of sites that can be assessed in a single year, without the sacrifice in accuracy and precision that usually accompanies measurement periods less than 1 year.

This remote wind measurement approach, using SODARs or LIDARs, as alternatives to met towers for WRA. These devices offer numerous potential advantages compared to traditional met towers, including their ability to measure the wind speed at hub height and are easily transported between sites, allowing for discontinuous measurement periods, but to distribute the measurement time at each site over the whole year, so that the total measurement period comprises smaller segments of measured data. **[3]**

Until recently, the accuracy and precision of SODAR and LIDAR have not compared favourably with cup anemometers that are generally used for site assessment. However, recent developments in SODAR data processing and new models of LIDAR indicate very close agreement with cup anemometry measurements. **[3]**

B-GIS based WRA (Significant GIS wind atlas and data bases)

Geographical information systems (GIS) are a powerful calculation and analytical tool of spatial variables. Among their main characteristics is their calculation capacity for matrices or grids, map algebra, where each unit of information or pixel is analyzed in relation to their neighbors and in connection with the remaining variables considered. **[4]**
Currently there are various GIS integrated WRA systems, especially for prospecting potential sites; these platforms whose primordial role is to create structured information databases and create dynamic scenarios of analysis, evaluation and integration of RE resources.

1-NREL Wind Atlas

Through the application of its wind mapping system, NREL has performed WRA and generated high-resolution wind maps for various areas of the world. The detailed wind maps and other resource data have facilitated the rapid identification of good wind resource areas and led to more successful prospecting and measurement efforts and facilitate the identification of areas where wind energy projects are likely to be feasible. **[6]**

2-The NASA/SSE: National Aeronautics and Space Administration (NASA)'s surface meteorology and solar energy (SSE) data set maintained in collaboration with the CAMNET Energy Technology Centre is an excellent source of renewable energy data. The SSE data, which is essentially an average over the entire area of the cell, may not represent a particular site within the grid. However, this database is an excellent and easy-to use source which could be used for preliminary studies of renewable energy systems. These data are a consistent 10-year global average on a 1º x 1º (about 100 km x100 km) grid. **[1]**

2-The CDC database maintained by the National Oceanic and Atmospheric Administration (NOAA) and the Cooperative Institution for Research and Environmental Sciences (CIRES) is another comprehensive source of weather and climatological information it is also a worldwide wind atlas generated with NOAA/CIRES-Climate Diagnostic Centre's (CDC) search engine (NCEP Reanalysis Product) The search mechanism in Climate Diagnostic Centre (CDC) allows one to collect a wide range of climate data from different sources. **[1]**

3-NCEP/NCAR Reanalysis: The NCEP/NCAR (National Centre for Environmental Prediction/National Centre for Atmospheric Research) Reanalysis project performs analysis of weather data from 1948 to the present using comprehensive methods of atmospheric modelling and forecasting.

4-COADS 2 deg. Standard: The comprehensive ocean-atmosphere data set (COADS) is an extensive collection of worldwide surface marine data gathered over the past two centuries. The basic observed variables by COADS include sea surface and air temperatures, wind, humidity, etc. Therefore, this map could be taken as a base map and a range (instead of a specific value) of wind speed could be attributed to each of the contour lines. **[1]**

C- Advanced methodologies for WRA

Synthetic Aperture Radar (SAR) imagery and Numerical Weather Prediction (NWP) are models which are the two best candidates for having a large coverage, with a significant accuracy and a good resolution. **[5]**
Systematic comparison studies between a mesoscale NWP model results and SAR images where done at a very coarse resolution of 15, 50 and 100 km in the past. **[5]**
These advanced WRA systems are the main sources for:

1-Physical systems Physical systems use the concepts of atmospheric dynamics and boundary-layer meteorology to carry out the spatial refinement of the coarse output of NWP systems to the specific site conditions. Two basic classes of physical systems:

- **Operational fluid dynamical simulations** similar to those of NWP systems.
- **Diagnostic models** which mainly use parameterizations of the boundary layer.

These procedures are based on numeric simulation with meso-scale models for long time period in site of interest using as an input reanalysis data, then the results should be validated against short period site measurement taking in to consideration measurement uncertainty (Which uses meteorological, topographical information and technical characteristics of wind turbines) **[4]**

2. Statistical systems (which uses explanatory variables and online measurements such as recursive least squares) or artificial neural networks (ANN) **[4]** or a combination of all three need training input from measured data.

NWP systems simulate the development of the atmosphere by numerically integrating the non-linear equations of motions starting from the current atmospheric state. On the other hand, statistical systems in one or the other way approximate the relation between wind speeds prediction and measured power output and generally do not use a pre-defined power curve.

For both types of wind power prediction systems, NWP provides the necessary input. In general, the weather services use one global model with a horizontal resolution ranging from 100 km^2 down to about 50 km^2 to capture the worldwide development of the weather systems **[7]**

Researchers recommend the following WRA steps for site selection for a wind turbine generator installation:

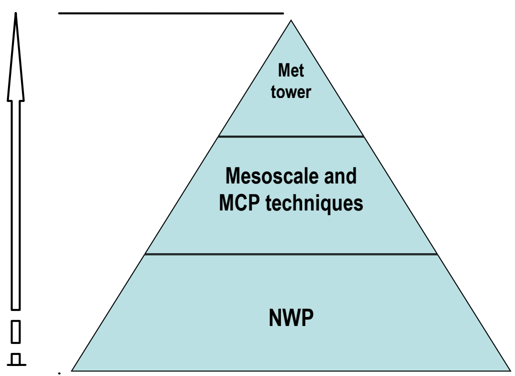

Fig.1 WRA steps in the ascending order of time scale and cost

They also progress from general regions to specific sites. One would start from a range of potential sites and eliminate sites after each step; finally, one site would be only left to carry out a wind measurement programme. **[4]**

Table 1 Uncertainty in wind using different approaches [18]

Method in predicting annual mean wind speed	**Uncertainty in wind speed,%**
Observational wind atlas (Mesoscale modelling)	10-30
Numerical wind atlas (Microscale modelling)	1-15
WAsP	2.0-5.9
ANN	1.7-6.8
MCP	5-10

3-WHAT IS NWP?

As NWP (Numeric Weather Prediction) systems extrapolate the actual state of the atmosphere using the laws of physics, the accuracy of the numerical predictions over the desired time horizon is typically far better than any type of statistical or climatologic approach which represents the average statistical behavior. Basically, the numerical models are divided into three classes: **[8]**

A- NWP models: 1000 km down to 10 km NWP systems do not explicitly simulate the complete range of atmospheric phenomena ranging from large-scale weather systems they only describe the dynamics of the atmosphere.

B-Mesoscale models: 10 km down to 1 km

A familiar tool of weather forecasting, mesoscale modelling offers a number of advantages for WRA, such as the ability to simulate, with reasonable accuracy, complex wind flows in areas where surface measurements are scant or non-existent. A mesoscale wind map shows wind variations throughout a large area (50–100 km resolution) neglecting the local effects such as orography, obstacles, surface roughness and thermally driven flows. **[1]**

The meso-scale models (KAMM, MASS, MM5, GESIMA, KLIMM, RAMS, Eta, Skiron, Mesomap, Wind Survey, MASS, GFS (global forecast system) are driven by large-scale NWP models and provide the boundary conditions.

One of the first was the KAMM-WAsP method developed by Riso. The output of the model, at a typical grid scale of 2-5 km, is used to drive WAsP, which produces wind resource estimates at a much higher resolution. **[9]**

Another model WindMap is based on the NOABL program, it normally operates at a grid scale of 100 to 200 m, which is roughly comparable to the spacing between turbines in wind projects. **[9]**

TrueWind Solutions developed MesoMap's mesoscale model which run in a dynamic mode with the energy equations. This allows the development of non-equilibrium mesoscale flows (sea breezes being an obvious example) within the model domain. **[9]**

The Mesoscale system has several major components:
First, there are the models: a mesoscale atmospheric simulation model (MASS, MM5) and a mass-conserving wind flow model (WindMap).

The second major component is a distributed computer processing system. A typical MesoMap project requires two CPU-years of processing; but it can be completed in about a week. Global meteorological data bases (reanalysis, surface, and rawinsonde) and geophysical data bases (topography, land cover, vegetation greenness, sea temperatures, snow cover, soil moisture) make up the third component.

The mapping process begins by defining several grids around the area to be mapped. The largest is typically more than 2000 km wide, with a mesoscale grid spacing of 30 km. Within that large grid there are usually two or three levels of nested grids, each covering a smaller area at higher resolution, with the last extending perhaps 200-400 km at a grid scale of 1-3 km.

The mesoscale model then simulates weather and wind conditions throughout the area at all levels of the atmosphere for 366 days randomly sampled from a 15 year period. The three-dimensional output of the model (including wind, temperature, pressure, and other parameters) is stored every hour of simulated time, resulting in a total of 8784 samples at each grid point.

The results of the mesoscale simulations are then summarized in data files containing gridded wind rose and Weibull statistics at different levels above the surface. These files are input into the microscale model.

Since surface measurement is generally done at various tower heights and dissimilar surrounding standardization of these data is necessary for further analysis. **[1]**

Typically, the root-mean-square discrepancy between model and data is 7-10%. After accounting for uncertainties in the data, the RMS error ascribed to the model alone usually falls in the range of 5-7%. To place this in perspective, the error margin in a high-quality measurement program is usually 3-4%. **[9]**

C- Micro-scale models: several 100 m down to 0.01 m

A micro-scale map, which is the ultimate goal towards selecting suitable wind sites, incorporates features such as, terrain conditions, roughness, land cover, vegetation, elevation, etc. to the mesoscale map. **[1]**

The most prominent example being the Wind Atlas Statistical Package, or WAsP, developed by the Riso National Laboratory of Denmark based on the theory of Jackson and Hunt (1975).This model creates a wind map and climatology of a region using data from a single reference mast. It and its cousins (MS-Micro, WindMap, SiteWind fromTrueWind and others) are best suited to estimating the wind resource in areas of simple to moderate terrain slopes at distances of up to tens of kilometres from the reference mast (Bowen and Mortensen, 1996; Walmsley, Troen, Lalas and Mason, 1990). **[9]**

4- Measure–correlate–predict (MCP) algorithms:

The goal of the MCP method is usually a characterization of wind speed distributions as a function of wind direction at the target site in order to be able to determine the annual energy capture of a wind farm located at the target site.

MCP is a statistical technique used for predicting the long-term wind resource at a candidate site by relating measurements from a short-term measurement campaign at the candidate site to long-term measurement at a reference site. **[4]** The long-term reference site data provide information about variations in the wind resource at time scales longer than the length of the target site data.

According to this method, surface data from short measurements or sparsely located stations (low quality ground data) are correlated with the global databases, which yields a prediction of site-specific wind condition **[1]** This is now the standard method adopted by the wind energy industry for assessment of suitable wind farm sites as long-term, on-site measurement campaigns are not financially viable, adding to the expense of and delaying wind farm development**. [10]**

In order to achieve good MCP, the measurement series at a target site has to be carried out within the same period of time as the long-term measuring series at the reference site; it is widely used and it complements the meso-scale models. **[11]**

MCP has been shown to provide more accurate estimates of the long-term wind resource at a site than simply assuming that the measured data alone as representative of the long-term resource. Measurement periods less than 1 year can also be used, the accuracy and precision of the predictions generally decrease as the measurement period decreases. **[13]** Therefore, 1 year of wind resource monitoring tends to be the standard measurement period in wind energy site assessment. **[3]**

The common procedure in the standard technique consists in; concurrent data sets of wind speed and direction measurements are obtained for the prospective wind farm site and for the Met-site. These are then split into groups according to the value of the direction sector measurement at the Met-site. **[10]** A regression relation between the speeds recorded at the measuring site and the Met-site is derived for each sector group. It is then assumed that these relations hold for all time and can be applied to the long-term sector mean wind speeds at the Met-site to derive long-term sector mean wind speeds at the measuring site.

Defining a relationship between the sites is complicated by stochastic variations in wind speed and direction over time and distance, the effects of terrain on the flow, time of flight delays, large-scale and small scale weather patterns, local obstructions and atmospheric stability. **[10]**

Although prediction of wind speed usually includes consideration of wind direction at the reference site wind direction is usually modelled independently of the wind speed. **[11]**

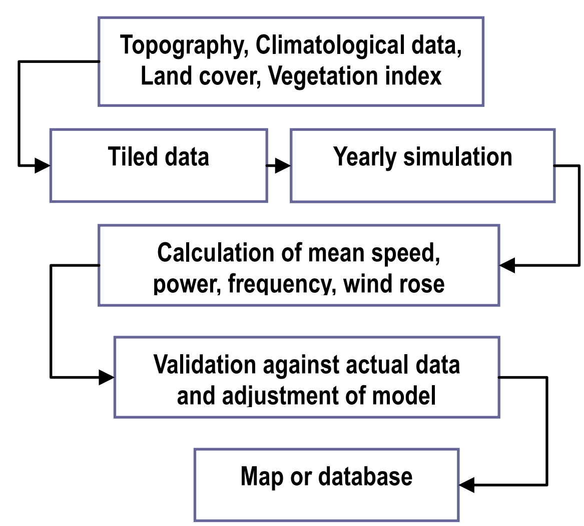

Fig 2-Conceptual block diagram of MCP method of wind map development [4]

Over the last 15 years well over a half a dozen variations on the MCP Techniques have been proposed, in part, to address some of the specific concerns mentioned above. These MCP algorithms differ in terms of overall approach, model definition, and use of direction sectors, length of data used for the documented validation effort, data used for validation effort, criteria used for evaluating the required length of concurrent data and criteria used for evaluating the effectiveness of the approach. The data may also be grouped or binned by other factors, such as the wind direction at the reference site. In this case, separate parameters are fit for each bin. **[11]**

Different MCP algorithms use different methods to fit the parameters. There are more than seven different MCP methods some of most poplars' are Derrick (Linear fit), Nielsen et al (Linear transformation), Mortimer (Speed distributions vs. linear models) A number of the methods mentioned above use linear regression. Linear regression is used for many problems it has the advantage that it can be easily implemented using available software and, if the linear regression assumptions apply, provides measures of precision, including confidence intervals. **[11]**

3-DYNAMIC RENEWABLE ENERGY MODELS

These are needed to assess and overcome the influence of uncertainties of RE generation on power system operation, such as coordinated production scheme, and a better understanding of RE resources and improved predictability of the state of the power system. Two different approaches to building mathematical models are as follows: **[12]**

A- Theory-Based Modeling. Here, the modeling is based on the established theories (from physical, biological, and social sciences) relevant to the problem. This kind of model is also called physics-based model or **white box model** as the underlying mechanisms form the starting point for the model building. **[12]**

B. Empirical Modeling. Here, the data available forms the basis for the model building, and it does not require an understanding of the underlying mechanisms involved.

As such, these models are used when there is insufficient understanding to use the earlier approach. This kind of model is also called data-dependent model or **black-box model.** In empirical modeling, the type of mathematical formulations needed for modeling is dictated by a preliminary analysis of data available. If the analysis indicates that there is a high degree of variability, then one needs to use models that can capture this variability. This requires probabilistic and stochastic models to model a given data set. Effective empirical modeling requires good understanding of:

A. The methodology needed for model building,
B. Properties of different models, and
C. Tools and techniques to determine if a particular model is appropriate to model a given data set. **[12]**

A variety of such models have been developed and studied extensively. One such class of models is the Weibull models. These are a collection of probabilistic and stochastic models derived from the Weibull distribution. These can be divided into univariate and multivariate models and each, in turn, can be further subdivided into continuous and discrete. Weibull models have been used in many different applications to model complex data sets.

The empirical modeling process involves the following five steps:

Step 1: Collecting data
Step 2: Analysis of data
Step 3: Model selection
Step 4: Parameter estimation
Step 5: Model validation

Once the correlation with meteorological station is established using long term registered data or reanalysis data ; we can say that the model is validated, therefore the prediction of wind resource at measurement site can be extrapolated in the surrounding sites using different systems.

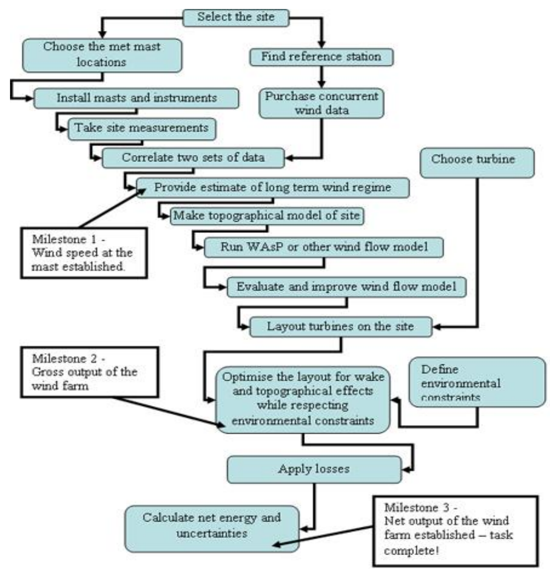

Fig. 3. *Overview of typical wind energy model, source (Garrad Hassan)* **[8]**

C-Limitations

The measurement and wind resource data is site specific, but with some restrictions it can be validated and extrapolated in the vicinity for simple terrain topography, for complex topography the uncertainty is very high. Basically this spatial and temporal extrapolation needs considering the terrain roughness, complexity and atmospheric parameters. Hence, the reputation and the value of energy would considerably increase, if fluctuations in the production of power were known in advance. This is exactly the purpose of power prediction systems to facilitate this information. The limitations in those uncertainties are considered finally in some lump sum correction over the net energy after calculating the output energy of the wind farm. The data collection and manipulation process also needs expensive investments; in addition to that it needs long-term historical serial of wind speed and direction data for at least 10 years, which means it will be difficult task to implement to any arbitrary remote region.

4-ADDITIONAL POSSIBILITIES FOR DECISION FLEXIBILITY

This issue must be explored, by both generation and DSM. In the context of variable production, variable demand, variable storage capacity; probabilistic decision methods should be promoted. Including a provision of stand by power back up for RE resource power fluctuations and forecast errors which also may impact the power system's short-term reserves. All sources of power system flexibility should be used and new flexibility and resserves sought.

A-UREM Optimization-model-based decision support systems

Optimization models are very crucial in the management of renewable energy systems because, it helps to take swift strategic and economic actions on the regional energy management decisions. Uncertainties in energy related parameters should be effectively addressed through appropriate stochastic approach.

One of exemplary models is (UREM, University of Regina Energy Model) Fig 4 it was proposed by researchers at University of Regina and widely applied across Canada at (national, regional, and community level). The objective function of UREM is to minimize the total costs associated with all types of energy activities/services in an energy management system, with all costs be discounted back to the year of decision maker's interests. In detail, it is a linear combination of varied costs related to technologies that moves energy carriers from sides of energy-supply to energy-demand. The application of this practical optimization model will help to analyze and visualize impacts of energy and environmental policies, regional/community sustainable development strategies, emission reduction measures and climate change in an interactive, flexible and dynamic context. **[13]**

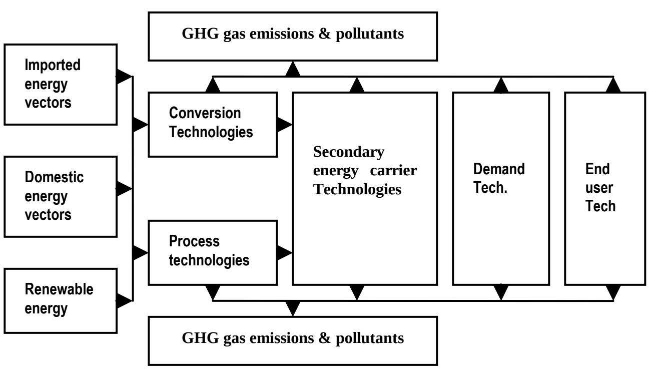

Fig.4 Structure of UREM **[13]**

B- Inexact community-scale energy model (ICS-EM):

This case study is conducted on three typical communities, which have varied economic and environmental costs for renewable energy supply and power generation. Conventional and renewable energy resources, relevant technologies and multiple end-use sectors, three time periods are considered, with each having an interval of 5 years. (Fig5.) Over the 15-year planning horizon, an existing renewable power generation system is available to meet electricity needs of the three communities. Facilities of micro-hydro, solar energy, and wind farm are available in the sub-system of power generation. **[14]**

In this study, the authors developed an inexact community-scale energy model (ICS-EM) for planning renewable energy management (REM) systems under uncertainty. This method is based on an integration of the existing interval linear programming (ILP), chance-constrained programming (CCP) and mixed integer linear programming (MILP) techniques. ICS-EM allows uncertainties presented as both probability distributions and interval values to be incorporated within a general optimization framework. **[14]**

The decision maker can formulate the problem as minimizing the expected value of net system cost with optimized capacity expansion planning schemes and resources allocation patterns. In an integrated REM system, a number of facilities/ technologies are available for energy production, conversion, transmission and utilization. For example, there are two types of technologies for power generation, including those utilizes renewable energy resources, as well as fossil fuel-based backups. Based on various policies, demand projections for every end-use sector can be analyzed. The facilities in the REM system have overall-cumulative limits while the energy demand amounts from the communities are flexible. **[14]**

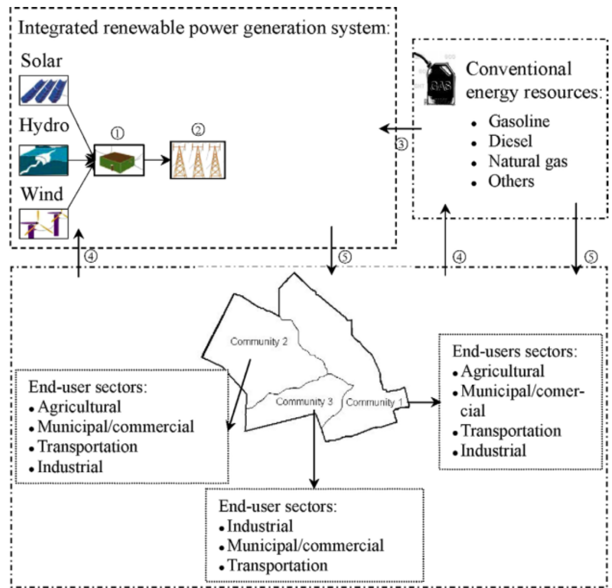

Fig.5 1-power conditioner and controller 2-local power distribution system 3-conventional power-generation facilities 4-policies, strategies and regulations 5-energy supply **[14]**

In order to address the above uncertainties (intervals and PDFs), the ILP and CCP methods are incorporated within ICS-EM. ILP is an effective method for dealing with uncertainties existing as interval values without distribution information. However, ILP cannot deal with uncertainties expressed as probabilistic distributions, such as availability of renewable energy resources. CCP, which can handle uncertainties that exist as random information, can thus be integrated with ILP, leading to an inexact community-scale energy systems model (ICS-EM). Multiple forms of uncertainties in ICS-EM can thus be tackled. **[14]**

The objective function of ICS-EM can be formulated as a function of:

- Costs of primary energy
- Availability of energy resources

- Electricity demand
- Capacity limits for power-generation facilities
- Technical constraints
- Capacity limits for conventional (backup)power generators

ICS-EM model can handle complexities that exist not only within an individual sector/process but also between each other in a REM system. Competitions among energy sources, power-generation technologies and resource availabilities can be reflected. Capacity expansion issues can also be addressed. However, CS-EM cannot reflect multiple forms of uncertainties, such as intervals and/or probability density functions (PDFs). For example, availabilities of many renewable energy resources (e.g., solar and wind energies) cannot be expressed in deterministic values; instead, are presented as probabilistic distributions. At the same time, for most of socio-economic factors in a REM system (e.g., energy prices, demand projections and capital investment costs), it is impractical and difficult to acquire PDFs. Instead, they may be expressed in intervals. Different formats of uncertainties thus exist in the decision making process, which should be incorporated within the formulation of ICS-EM. **[14]**

AKNOWLEDGEMENTS

Government of Spain, especially AECID-MAE has contributed financially to my professional formation. My adviser Dr. J.Antonio Dominguez Navarro and Dr. Immaculada Arauzo Pelet the RE course coordinator have contributed with due follow up and mentoring. I would to thank all those partakers without exception.

CONCLUSIONS

The so-called fluctuating or intermittent nature of the RE power production due to unforeseen variations of the atmospheric conditions constitutes a challenge for the players on the production and distribution and demand side of the electricity supply system. This limitation is often used as an argument against the utilization of RE power.

The paper explained different WRA methodologies, energy models and optimization models which are common and some emerging methodologies, which can accelerate the future of wind resource energy systems integration. There are many state of the art short term WRA and prediction approaches which go hand on hand with those explained methodologies but, are not included because the main focus as indicated above was the long term assessment issue.

Many reliability, cost and rapidity issues have improved radically since the introduction of latest remote assessment procedures. These are only some indicators of a significant level of progress in the wind energy integration issues even though there are still many weaknesses that should be overcome developing adequate tools in order to continue gaining broader ground.

REFERENCES

[1]- Wind energy resource map of Newfoundland, M.J. Khan, M.T. Iqbal Renewable Energy 29 (2004) 1211–1221, 2003 Elsevier Ltd

[2]- Martín Gastón, Edurne Pascal, Ignacio Marti, Uxue Irigoyen, Elena Cantero, Sergio Lozano, Yolanda Loureiro, Wind resources map of Spain at mesoscale. Methodology and validation,Wind Energy Department, National Renewable Energy Centre (CENER) C/Ciudad de innovación, 31621 Sarriguren, Navarra Spain 2006

[3]- Matthew A. Lackner, Anthony L. Rogers, James F. Manwell, The round robin site assessment method: A new approach to wind energy site assessment, Renewable Energy 33 (2008) 2019–2026) Elsevier

[4]- R.D. Prasad1 R.C. Bansal2 M. Sauturaga3, Some of the design and methodology considerations in wind resource assessment Published in IET Renew. Power Gener, 2009, Vol. 3, No. 1, pp. 53–64 53 doi:

[5] Philippe Beaucage et.al, Wind Assessment Using Synthetic Aperture Radar (SAR) Satellite and the Mesoscale Compressible Community (MC2) model, Institut National de la Recherche Scientifique (UQ), 1650 Lionel-Boulet, Varennes (Qc), J3X 1S2, Canada, Phone (450) 929-8151

[6]- D. Elliott is with the National, Harnessing Untapped Wind Power Worldwide panel session, 2002 IEEE PES Winter Meeting. Renewable Energy Laboratory, Golden, Colorado, USA.

[7] Dr. Matthias Lange, Ulrich Focken, Physical Approach to Short-Term Wind Power Prediction**,** Springer-Verlag, Berlin, Heidelberg 2006.

[8]http://www.wind-energy-the-facts.org/en/part-i-technology/chapter-2-wind-resource-estimation/local-wind-resource-assessment-and-energy-analysis/the-prediction-of-the-energy-production-of-a-wind-farm/energy-production-prediction-methodologies.html

[9]- Michael Brower, J. W. Zack, B. Bailey, M. N. Schwartz, and D. L. Elliott, Mesoscale modelling as a tool for wind resource assessment and mapping, TrueWind Solutions, Albany, NY, and National Renewable Energy Laboratory, Golden, CO

[10]- A new matrix method of predicting long-term wind roses with MCP J.C. Woods*, S.J. Watson, Journal of Wind Engineering and Industrial Aerodynamics 66 (1997) 85-94 1997 Published by Elsevier Science

[11]- Anthony L. Rogersa, John W. Rogersb, James F. Manwella, Comparison of the performance of four measure–correlate–predict algorithms, Journal of Wind Engineering and Industrial Aerodynamics 93 (2005) 243–264, 2005 Elsevier

[12]- D.N.P. Murthy, Min Xie, and Renyan Jiang ,Weibull Models,ISBN 0-471-36092-9, 2004 John Wiley & Sons, Inc.

[13]- Y.P.Cai, G.H.Huang, Q.G.Lin,X.H. Nie,Q. Tan,An, optimization-Model-Based interactive decision support system for regional energy management systems planning under uncertainty. Doi:10.1016/j.eswa.2008.02.036, Elsevier Ltd.

[14] Y.P. Cai et al**.** Community-scale renewable energy systems planning under uncertainty an interval chance-constrained programming approach. Renewable and Sustainable Energy Reviews (2008)