
# DECENTRALIZED POWER PLANNING: A REVIEW OF MATHEMATICAL MODELS

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## ABSTRACT

A description of the mathematical models used in decentralized energy planning is made in order to examine the models applied, their limitations, applications and trends. After the 90's, the literature showed a clear change of paradigm in the decentralized power planning. This new paradigm is characterized by the inclusion of more than one criteria or objective evaluation, which makes the planning a multidimensional process. In this regard, we found evidences to demonstrate the relevance of Multi-criteria Decision Making models for decentralized energy planning.

**Key words:** Decentralized generation, mathematical models, power supply, planning, rural.

**1. - INTRODUCTION**

The energy can meet basic human needs: cooking food, providing light, providing heat and hot water and extract water. Energy is the basis of almost all economic activities, whether for food, transport, market, or simply raw materials to produce or provide other products and services. However, there is an important part of the world's population, most of it in developing countries, which lack access to modern energy (electricity).

Currently, 1600 million people worldwide have no access to electricity, 80% of them live in rural areas [1]. The world's population and electricity demand will grow. If rural electrification is not accelerated, the number of people without access to electricity will remain almost unchanged [1]. According to the International Energy Agency (IEA) [2] in the last 15 years, the number of people without electricity has been reduced from 2.0 billion in 1990 to 1.6 billion in 2005, with China registering the fastest progress. Excluding China, the number of people without electricity has increased steadily over the last 15 years. Due to the constant growth of population, if they do not put in practical on new policies, it will continue existing 1400 million persons without access to the electricity in 2030.

On the other hand, the problems of energy planning are complex, in which multiple decisions and criteria are converging [3]. The power supply to the rural poor in developing countries is a complex activity that goes beyond the simple solution of the best technology [4]. Evaluation methods often emphasize only a few aspects of the local energy problem [4]. In this regard, the decision making process of rural energy, in most cases, neglected the factors that actually affect the rural electrification, since the majority of the proposals have not taken into account the population's need [4]. Moreover, in most developing countries have not paid adequate attention about rural development, especially to the needs of modern energy. Hence the importance of identifying a consistent and systematic energy planning to improve access to modern forms of energy.

Consequently, a review of the methods or mathematical models is carried out to provide information about the problem formulation of decentralized energy planning (DEP), limitations, scope and trends, which allow us to discuss elements, if indeed, the methods have been used over the past 30 years can ensure a consistent and systematic approach (DEP) to needs and local means that imply the access to the modern energy.

## 2. - RURAL ENERGY PLANNING: DECENTRALIZED ENERGY

### 2.1 Overview of decentralized energy

The electrification of rural areas has gone through various stages or moments. Different factors, including political, economic, social and environmental concerns have influenced the shape, type, method and model to promote or facilitate the power supply.

Several researches [5] [6] [7] [8] shows that the centralized power generation significantly dominated the pattern or model of electricity supply. The first formal development of energizing rural areas was done using the model of urban areas [5]. Indeed, the extension of distribution networks has been and remains the dominant model of bringing electricity to rural and remote areas. The technical and economic criteria [4] [5] [9] [10] have been the dominant features in the proliferation of power systems to remote rural populations. The extension of the distribution network has enabled a considerable number of villages to benefit from the availability of this modern form of energy. In contrast, [5] [11] [12] the partial or total blackout cuts, the cost of energy, network's maintenance lack, social and environmental impacts, high costs of investment in new facilities, availability finite financial resources and the emergence of new power technologies such as distributed generation (DG) have been paving the success of this proposal.

The emergence of DG has brought a new vision of generating and/or provides power for applications that require on-site power in an affordable, secure and less social and environmental issues regarding the extension of distribution networks.

The DG by fossil fuels and renewable energies have opened the way for this new trend or pattern of energy supply. The benefits reported in [6] [7] [11] [13] [14] are impressive, for example, the GD prevents or reduces the energy losses that occur in the distribution network. They are also modular, relatively easy to install, some technologies are mature and are lower investment costs and operation, among others. Consequently, it appears that these benefits are leading to a significant shift in electrification's paradigm; one aspect that surely must be taken into account in the planning of future power's supply systems in rural and remote areas of developing countries.

Moreover, energy planning at the decentralized level is a matter of recent origin. Understanding their progress and current status happens to know the energy models and its relation to energy planning. Indeed, Hiremath et al. [15] consider the decentralized energy planning is a very new concept with limited applications.

The DEP purpose involves preparation of an area based on the planning of local energy resources (all sources) and converting equipment (technology) to meet their energy needs at a minimum and environmental cost (eco-efficient).

**2.2 Overview of energy models**

Energy models (expressed in mathematical models) are, as other models, a simplified representation of a real system. The models are useful because they allow us to represent complex systems that are beyond the capacity of the human brain to comprehend and understand. Indeed, these models can be used to perform comprehensive calculations and analysis of the system [15].

Mathematical models have played a decisive role in the broad field of planning. The use of computers has contributed to this development, as they allow relatively fast and automatic processing of information [16].

A large number of models have been developed to carry out the analysis of energy systems. These models are based on different approaches and use a wide range of tools and/or mathematical methods, which have been described below.

Mathematical model used for energy planning are: Linear Programming (LP), Multiple Criteria Decision Making (MCDM), Multi-objective Programming (MOP), Nonlinear Programming (NLP) and Dynamic Programming (DP).

Linear Programming is a set of rational techniques of analysis and problem solving that aims to help managers in decisions on matters which involve a large number of variables [17]. The PL is applied to optimization models in which the objective functions and restrictions are strictly linear [18]. The PL's first offer was made in 1939, thanks to the contribution of mathematician and economist L.V. Kantorovich. Then, in 1947, Dantzing and Wood developed and implemented the first general problem of linear programming. Furthermore, LP is divided into: classical linear programming, integer linear programming (ILP), mixed integer linear programming (MILP) and multi-objective linear programming (MOLP).

Multiple criteria decision making (MCDM) is a generic term for all methods that exist for helping people making decisions according to their preferences, in cases where there is more than one conflicting criterion [19]. Using MCDM can be said to be a way of dealing with complex problems by breaking the problems into smaller pieces. After weighing some considerations and making judgments about smaller components, the pieces are reassembled to present an overall picture to the DMs [20]. MCDM allows decision makers to choose or rank alternatives on the basis of an evaluation according to several criteria. Decisions are made based on trade-offs or compromises among a number of criteria that are in conflict with each other [21] [22]. Multiple objective decision making (MODM) and multiple attribute decision making (MADM) are the two main branches of MCDM [23].

MODM methods are multiple objective mathematical programming models in which a set of conflicting objectives is optimized and subjected to a set of mathematically defined constraints. The purpose is to choose the ‘‘best’’ among all the alternatives [24].

MADM or MCDA (Multi-criteria decision analysis) refers to making preference decisions by evaluating and prioritizing all the alternatives that are usually characterized by multiple conflicting attributes [25]. By using MCDA methods, DMs should feel that all important criteria have been properly accounted for. This should help to reduce the post-decision regret [26]. Ideally, the MCDA methods will help the DMs to understand and identify the fundamental criteria in the decision problem, and avoid making important decisions out of habit [3]. MCDA are subdivided into several types: Analytical Hierarchy Process (AHP), Compromise Programming (CP), Goal Programming (GP), TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution), PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations), ELECTRE (Elimination Et Choix Traduisant la Realité, in French), MAUT (Multi-Attribute Utility Theory) and MAVT (Multi-Attribute Value Theory).

The analytic hierarchy process (AHP) is a methodology consisting of structuring, measurement and synthesis, which can help decision makers to cope with complex situations [27] [28]. It is a descriptive decision analysis methodology that calculates ratio-scaled importance of alternatives through pair-wise comparison of evaluation criteria and alternative. It involves decomposing a complex decision into a hierarchy with goal (objective) at the top of the hierarchy, criteria and sub-criteria at levels and sub-levels of the hierarchy, and decision alternatives at the bottom of the hierarchy [29]. The Compromise programming (CP) defines the best solution as that located at the set of efficient solutions, which point represents the shortest distance in relation to an ideal point [22]. To measure the degree of proximity of an efficient point with respect to the ideal point in the analysis introduces a distance function. Under the compromise programming approach, the concept of distance is not used only in a geometrical sense, but rather as a derivative of human preferences. The GP is a technique to solve models with multiple objectives. The main idea is to convert the various targets in a single original goal. The resulting model produces the so-called efficient solution because it could not be optimal with respect to all the conflicting objectives of the problem [30]. The principle of TOPSIS [31] is that the selected best alternative should have the shortest distance from the positive ideal solution in geometrical sense. The TOPSIS method assumes that each attribute has a monotonous increase or decrease. This facilitates locating the ideal solution and negative ideal solution. Thus, the order of preference of the alternative is produced by comparing the Euclidean distance [32]. ELECTRE is capable of handling discrete criteria and qualitative and quantitative nature and it can provide a complete ordering of alternatives [32]. The method considers the relationship of superclasificación depending on the number of targets in which one alternative is strictly superior to another and the importance of these objectives. It is done through a weighting of the objectives set by the decision maker [33]. The elimination and choice translating reality methods, including ELECTRE I, II, III and IV methods, are a family of outranking methods [23] [34]. PROMETHEE method developed by Brans [35] has been used in energy planning and different applications. This method uses the outranking principle to rank the alternatives, combined with the ease of use and decreased complexity. It is well adapted to problems where a finite number of alternatives are to be ranked considering several, sometimes-conflicting criteria. PROMETHEE are also a class of outranking methods. It introduces the preference functions to measure the difference between two alternatives for any criteria [29]. Multiple attribute utility theory (MAUT) allows decision makers to consider their preferences in the form of multiple attribute utility functions [36]. A special case of MAUT is multiple attribute value theory (MAVT) where there is no uncertainty in the consequences of the alternatives.

The MOP methods are subdivided into several types: Classical Multi-objective Programming (CMOP) and Programming with Multi-objective Evolutionary Algorithms (MOEA).

CMOP is useful when the preference information is very detailed and the purpose of planning is to find a solution that represents [9]. However, these methods have drawbacks. Both the weighted sum approach and the method of constraints can be time consuming calculation due to the large number of targets [37] [38]. The solutions found by the weighted sum method are strongly dependent on the shape of the Pareto front and the form of aggregation of the objective function [37].

The MOEAs methods are a natural way to solve multi-objective problems efficiently, because this method to work in parallel on a set of solutions have the potential to address problems with multiple objectives, finding in each run a set of approximate solutions to the Pareto front, incorporating a elitism value of the algorithms. They are also less sensitive to the shape or continuity of the Pareto front and allow approaching problems with space of solutions of great size or dimensioning [39]. MOEAs stand out in this task and have been applied in many papers [39]. One of the most important characteristic of this kind of algorithms is the concept of Pareto optimality [39]; thanks to this, as a result of the optimization process, a set of possible solutions is obtained after a search process in which the objectives involved in the design are evaluated independently. The designer can select the ones he/she thinks most appropriate depending on the values of the considered objective from among the solutions obtained [40].

Nonlinear programming (NLP) is the process of solving a system of equalities and inequalities subject to a set of constraints on a set of unknown real variables, with an objective function to optimize, when some of the constraints or the objectives functions are not linear. NLP provides a set of tools that operate on strictly spaces seeking solutions to problems. In addition, NLP allows the modeling of nonlinear constraints. The methods of NLP are the one-variable optimization, multivariable optimization with no restrictions and multivariable constrained optimization. The quadratic programming is considered a special case of NLP.

Dynamic programming (DP) is a mathematical technique invented by Bellman in 1953, which is used to solve mathematical problems which are selected in a series of decisions taken in sequence. This type of programming is the optimal solution of a problem with "n" variables breaking it down into "n" stages, each stage a one-variable sub-problem. However, the nature of the stage differs according to the optimization problem; the PD does not provide details of computation to optimize each stage [18]. The PD can reduce the runtime of an algorithm using overlapping problems and superstructures optimal. Its main application is in optimization problems. On the other hand, dynamic programming can be approached in two ways: as deterministic and stochastic or probabilistic way.

**3. - METHODOLOGY**

As we have seen, the rural electrification from isolated or remote areas is a potential of distributed generation widely cited in the literature. This application is not important actually but it could become so in the next years. Evidence gathered so far allow us to infer that there are sufficient elements for a change in this regard. Hence the importance of knowing the mathematical tools that have been implemented and new trends that could improve the method or model of electricity supply planning and the benefits for future users.

Universal access to modern energy, overcoming poverty, climate change and the development of distributed generation technologies, among others, could be promoting a change in the form of decentralized energy planning. One change that could be characterized by the inclusion of more criteria and/or objectives that allow a more comprehensive assessment of the problem: “multidimensional assessment".

Here, a review of the literature since the late 70's to 2010 has been performed. The literature, some 113 publications related to energy planning (in general) was obtained from published scientific articles. Key-words used for such purposes were: energy planning, decentralized energy, sustainable energy, multi-criterion and multi-objective planning.

The studies consulted were organized and classified by year of publication, author, country, mathematical model and application, type of mathematical model and method or criteria used. The models found have been classified into five (5) categories (family of models) and 13 types of methods.

**4. - RESULTS AND DISCUSSION**

Of the 113 articles surveyed, from 70's to the present (2010), 43 researches were directed at developing countries, which represents 38.05% of the literature. Of these works (DEP), none of them made before 1980.

Of the literature focused on DEP, only 3 studies (7.0%) belong to the 80's, 19 publications (44.2%) to 90's and 21 to the first decade of 2000 (48.8%) (See figure 1).

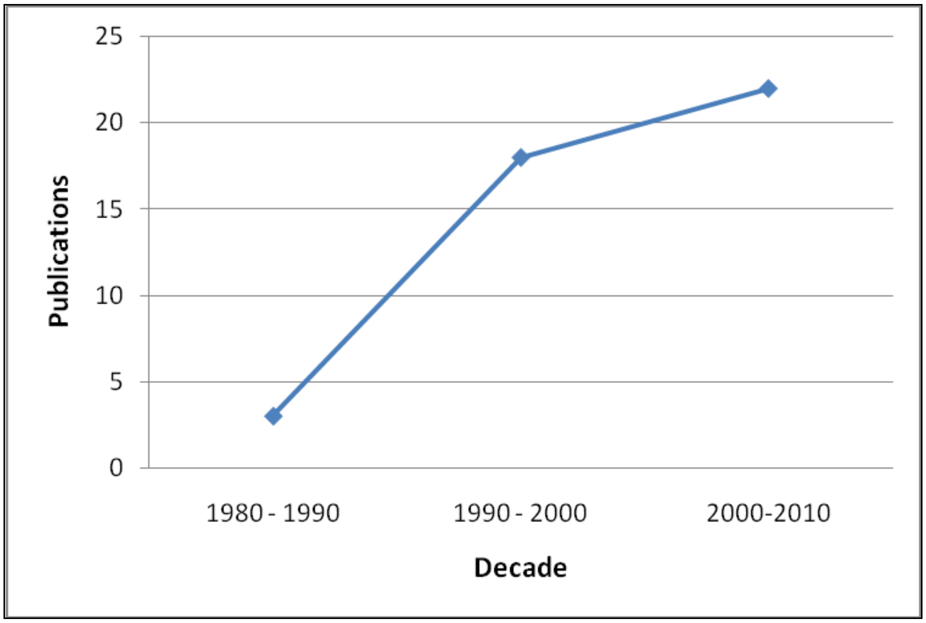


**Figure 1**. Numbers of papers published in DEP

The countries with the most contributions in this field of research are: India (53.4%), followed by Spain (4.7%), Colombia (4.7%), China (4.7%), United States of America (4.7%) and Tunisia (4.4%), among others (see figure 2).

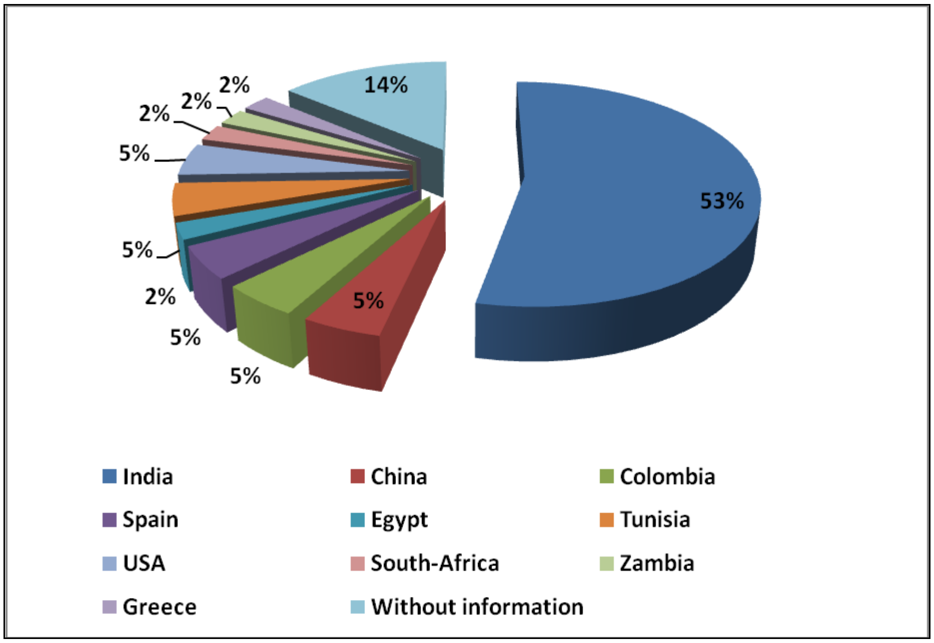


**Figure 2.** Country of publication or location of case study in DEP

Then, in Figures 3, 4, 5 and 6 are shown the mathematical models used in the literature. These models are divided into 5 categories (described above), which correspond to the following: Linear Programming (LP), Decision Making Multi-Criterion (MCDM), Multi-objective Programming (MOP), Nonlinear Programming (NLP) and Dynamic Programming (DP).

From the literature reviewed, 45 mathematical applications have been identified. Linear programming has been and remains the most widely used model (42.2%), followed by MCDM (28.9%), Multi-objective Programming (15.6%) and Nonlinear Programming (8.9%), respectively. Thus, the dynamic programming model has been less used (4.4%).
Similarly, a classification by type of mathematical model indicates that LP model has been the most used (42.2%), followed by GP (15.6%), MOEA (11.1%), NLP (8.9%), AHP (6.7%) and CP (4.4%), among others.

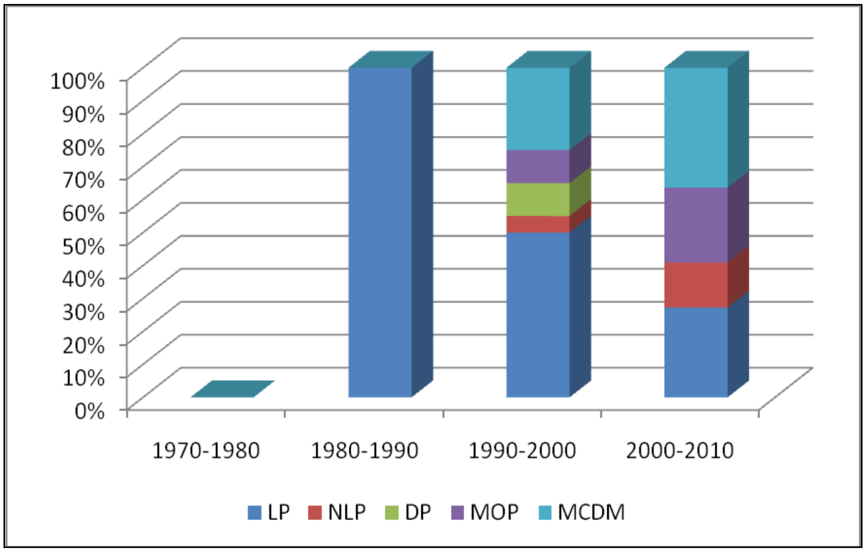


**Figure 3.** Categories of mathematical models used in the DEP

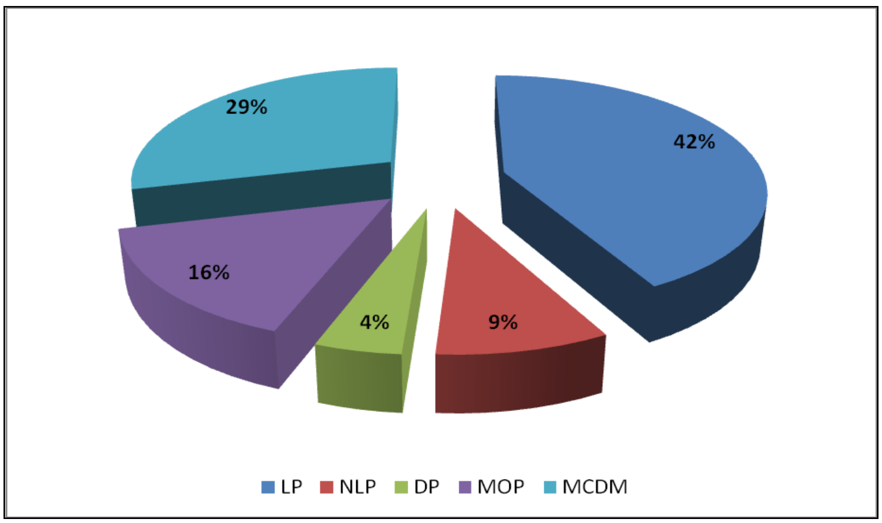


**Figure 4.** Distribution by categories of mathematical models used in DEP (1970-2010)

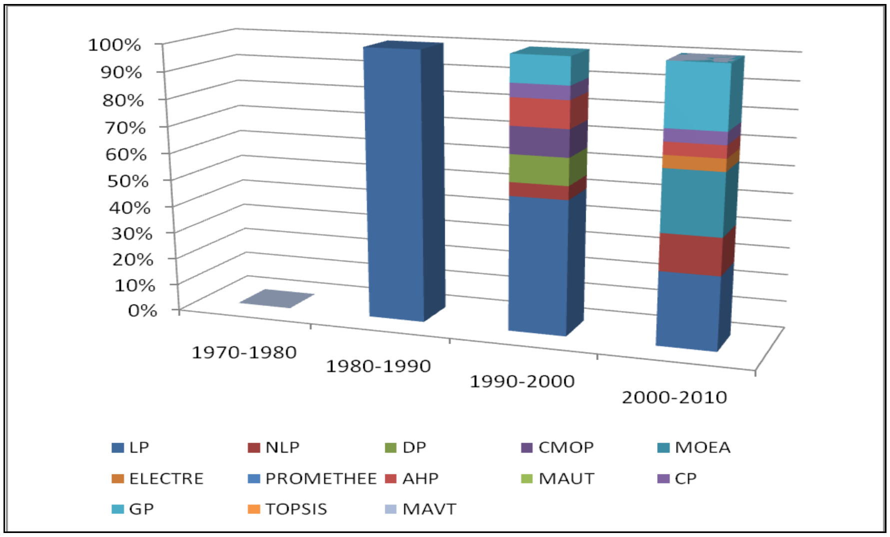


**Figure 5.** Mathematical models used in the DEP

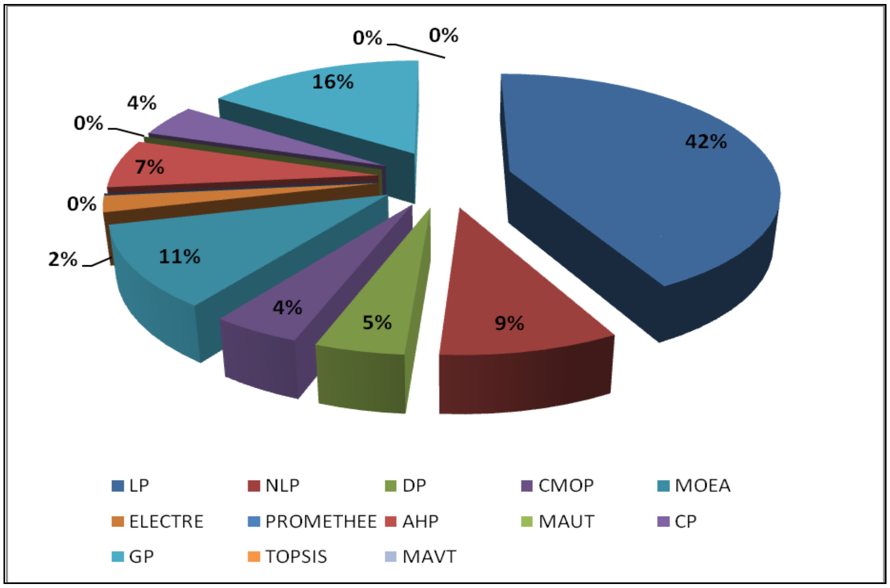


**Figure 6.** Distribution by types of mathematical models used in DEP (1970-2010)

Referring to the models of Multi-criteria Decision Making, its implementation has been significant since 1990, being more widely applied in the first decade of 2000. In this regard, the studies published in the 90's, which used MCDM, accounted for 25% of the literature and for the next decade by 36%. En absolute form, the authors have used these models from early 90's until late 2010; they have raised the percentage distribution of application from 11.1% (1990-2000) to 17.8% (2000-2010), for the four decades of study.

Planning by Multi-objective Programming has also been heavily involved. The first studies published that have used this method, also correspond to the 90's. Indeed, interest in the application of this model has been renovated from a 10% between 90's up to 22.7%, today (2010). An interesting aspect of this model is the appearance of MOEA early in first decade of 2000, displacing completely the application of classical multi-objective programming.

Nonlinear Programming also has been used significantly in recent years. In this sense, the studies published in the 90's have gone from 5% up to 13.6%, currently (2000-2010).

In relations with the application area of these models, in Figure 7 is evident that a large proportion of them have been widely applied in the selection of technologies and/or allocation of energy resources in developing countries. Of which, LP and MCDM models have been widely used (41% and 29%, respectively).

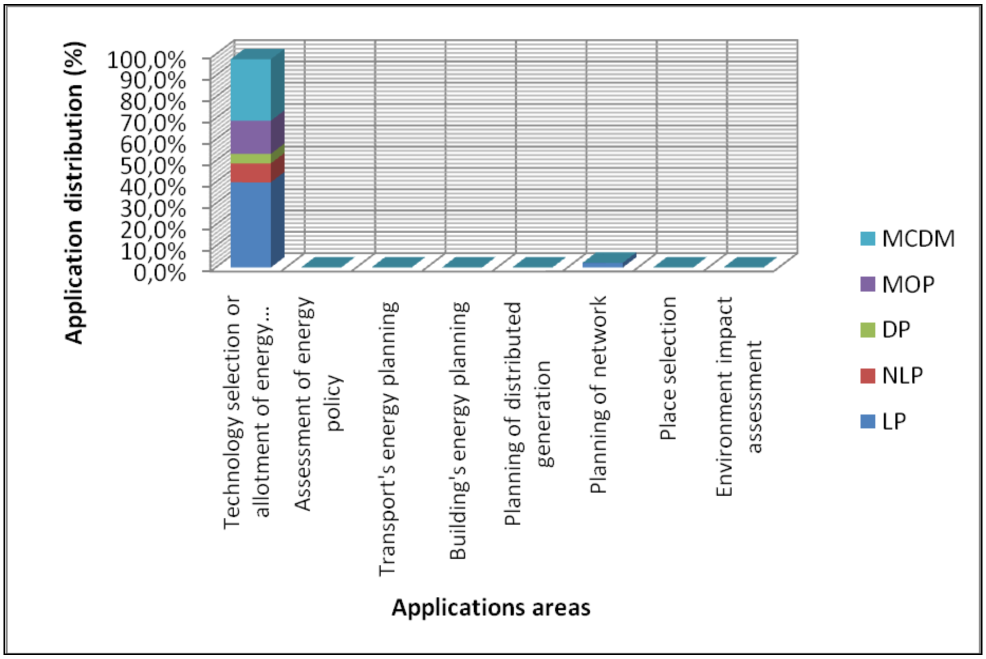


**Figure 7.** Application area of mathematical models used in the DEP (1980-2010).

Referring to the planning horizon used in these mathematical models, both short (65%) and medium term (26%) were the most widely used time intervals in the literature (see figure 8).

From figure 9 is evident that although the 90's have been considered others planning horizons than the short term (ST), long-term planning (LT) has been little explored.

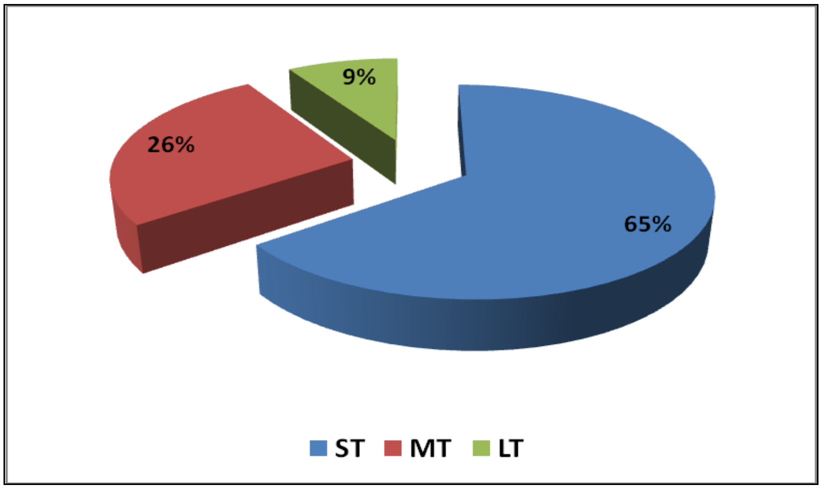


**Figure 8.** Distribution of time horizon in DEP (1980-2010)

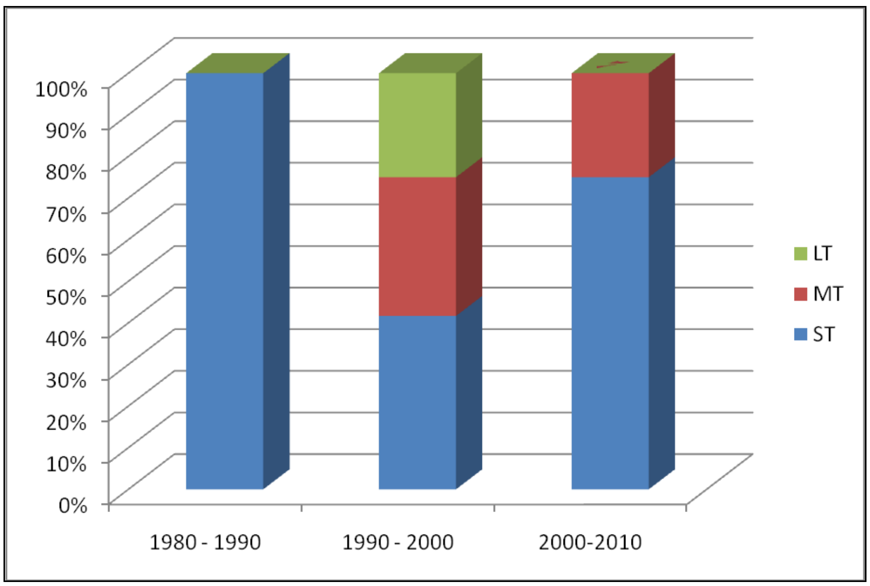


**Figure 9.** Horizons of planning used in DEP

A review of the objectives and/or criterions used in the decentralized energy planning shows that the economic approach has been the most widely used in the three decades of study (100% of the literature). However, both the 90's and in the next, the economic approach has been supplemented by other criteria, including technical preferably. However, at present, the authors have included a higher priority in other relevant criteria such as environmental and social (see figure 10).

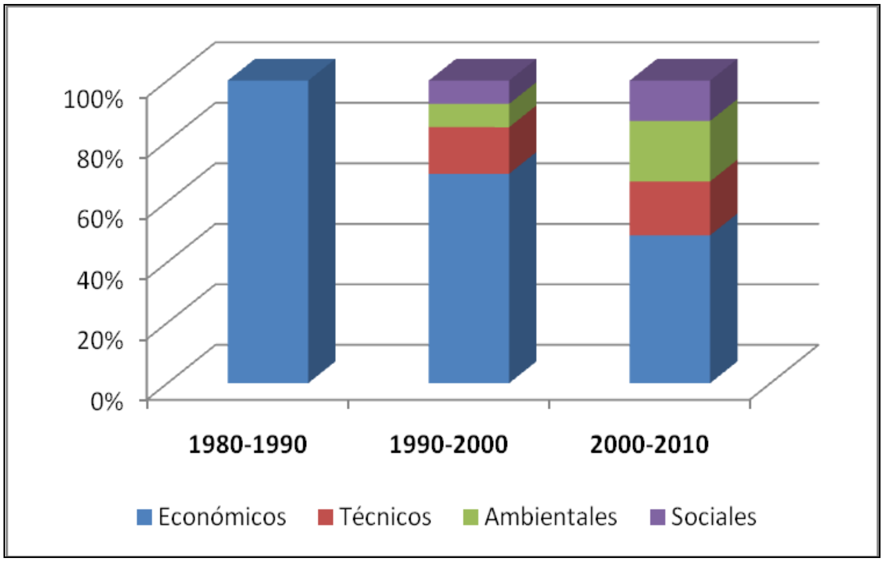


**Figure 10.** Criterions used in DEP

The results of this research clearly show that the Linear Programming, in spite of being the most widely used model in the last three decades, shows a significant decline in their use. Some causes of this decline may be associated with increased penetration and/ or application of MCDM models and MOP. Additionally, the inherent limitations of the LP in decentralized energy planning, for example, mono-dimensional optimization, could be the source of the emergence of a new trend in the planning of energy systems.

Mathematical methods, inherent power planning in rural or remote areas, have focused mainly on the consideration of a single criterion or objective. Of these, the economic criterion, expressed as the minimization of total costs, is one of the most common targets.

The consideration of a few criteria or goals in the problem modeling of energy planning, makes the planning context very simplified, which could be categorized as a one-dimensional planning. In contrast, the problems of energy planning are complex where there are usually multiple decision makers, multiple criteria or objectives, which warrant the use of more complete and robust methods.

In this context, and given that the planning of power systems represent a multidimensional problem, its mathematical expression is multi-multi-objective or multi-criteria nature. Therefore, MCDM could be a convenient method for such purposes.

Specifically in the field of decentralized energy planning, its growing and relatively recent interest in using models belonging to the family MCDM, suggest that these models provide better results in the power's systems planning.

Similarly, it appears that MCDM models are more convenient to use when planning area is directly related to energy resource allocation, selection of technology or configuration of energy supply mix.

With regard to the family of MCDM models, the increased use of Goal Programming, Analytic Hierarchy Process and Compromise Programming, we suggest they could be the most appropriate models for energy planning in the rural area and remote areas, specifically in the smaller territorial units such as villages.

This new trend in the use of mathematical models for DEP shows a clear paradigm shift after the 90's, in the planning approaches of DEP. This new paradigm is characterized by the inclusion of more than one criterion and/or objective assessment, which allows the planning takes into account other aspects different to economic or technical criteria, going from a single level planning for multi-dimensional level planning.

**5. - CONCLUSIONS**

Referring to the mathematical models used in DEP from the developing countries, there is scientific evidence that suggests a paradigm shift, after 90's, in the planning of electricity supply in rural and remote areas.

Energy planning at the decentralized level is a matter of recent origin. The first published papers on this topic (very few), at the beginning of 80's and a proliferation of the same after 90's confirm this.

The applications of decentralized energy planning, to rural and remote level (villages), are limited. A volume of published of less than two (2) articles per year to prove it.

The criteria for analysis and/or decision covered so far (techno-economic) are not sufficient to outline an energy system adapted to local environmental conditions. Environmental and social considerations, very little addressed so far, demonstrate the lack of consistency in the planning of decentralized energy systems. Therefore, a new proposal for decentralized energy planning (modern planning) is required.

Consistent with the need to include new approaches in energy planning, the long-term time horizon should also be explored in more detail to clarify the benefits to be accrued in both the social and environmental.

In general, a coherent and robust planning can bring important benefits. Consequently, it can provide better information for decision makers have the opportunity to decide for a suitable system with the environment (energy and environmental resources) and the needs of local people (services). Also, a correct decision could provide a better use of financial resources (public and private) to invest, and improved quality of life for its beneficiaries.

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