Sustainable Policy Making: A Strategic Challenge for Artificial Intelligence

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■ *Policy making is an extremely complex process occurring in changing environments and affecting the three pillars of sustainable development: society, economy and the environment. Each political decision in fact implies some form of social reactions, it affects economic and financial aspects and has substantial environmental impacts. Improving decision making in this context could have a huge beneficial impact on all these aspects. There are a number of Artificial Intelligence techniques that could play an important role in improving the policy-making process such as decision support and optimization techniques, game theory, data and opinion mining and agent-based simulation. We outline here some potential use of AI technology as it emerged by the European Union (EU) EU FP7 project ePolicy: Engineering the Policy Making Life Cycle, and we identify some potential research challenges.*

Public policy issues cover a wide variety of fields: economy, education, environment, health, social welfare, and national and foreign affairs. They are extremely complex, occur in rapidly changing environments characterized by uncertainty, and involve conflicts among different interests. In the modern world, due to globalization, the political activity and intervention become more widespread, and so the effects of its interventions become more difficult to assess. At the same time it is becoming ever more important to ensure that actions are effectively tackling the real challenges that this increasing complexity entails.

Generally speaking, the policy-making process traverses four steps: policy planning, environmental assessment, implementation, and monitoring. The first three steps are performed ex-ante. In the planning step, strategic objectives are set, budget constraints are defined, geophysical constraints are considered. The assessment phase, which is traditionally performed after the planning step, concerns the

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evaluation of the impact of the policy plan on the environment, and to a certain extent on economy and society. Implementation consists of defining a set of instruments to support the planning objectives, such as incentives, information campaigns, tax exemption, and compulsion (to name a few). The monitoring step is performed ex-post, to check whether the implementation strategies achieve the expected objectives settled during the planning phase.

There are a number of problems in this process at present. First, the planning step and the environmental assessment are performed in sequence: in case a plan contains negative effects on the environment, only corrective countermeasures can be applied a posteriori. If planning and environmental assessment were performed at the same stage, an environmentally well-assessed plan could be produced instead. Second, the implementation instruments are decided without any proper strategy nor assessment of their effect on the society. These effects are indeed checked during the monitoring phase to measure whether they are conformant with the planning objectives in an ex-post fashion. Third, the steps are always performed manually with no (or very little) information and communications technology (ICT) support.

We strongly believe a number of AI techniques could be effectively used for aiding governance and policy making: the literature reports attempts to use agent-based simulation (Troitzsch et al. 1999), opinion mining (Pang and Lee 2008), visual scenario evaluation (Chamberlain et al. 2012), and optimization (Cattafi et al. 2011) to support specific cases of this process, but there is large space for improvement. What is totally missing at present is a comprehensive tool that assists the policy maker in all phases of the decision-making process. The tool should compute alternative scenarios each consisting of both a well-assessed plan and the corresponding implementation strategies to achieve its objective. We need a tool that is able to integrate and consider, at the same time, global objectives and individual/social reactions. These two perspectives could be, and often are, in conflict, and possibly game theory could be used to find an equilibrium between the two parts.

The schema we devise is depicted in figure 1. Moreover, the policy maker should take into account the global view of the policy, namely financial aspects, objectives, environmental impacts, and constraints and generate alternative scenarios. On the other hand, the society can participate in the policy-making process through e-participation both in the ex-ante phase during the definition of the policy and in the ex-post phase for providing feedback on different scenarios. Clearly, we should be able to come out with an equilibrium between the global and the individual point of view. In this case game theory could play a role.

The ideas expressed in this article are a result of the EU FP7 project called ePolicy: Engineering the Policy Making Life Cycle which focuses on developing decision support systems for aiding policy makers across all phases of the policy-making process. In the following, we will discuss some AI techniques and how they can be used to aid specific parts of the policy-making life cycle

Policy Planning

Policy planning is the science of efficient placement of land use activities and infrastructures for the sustainable growth of a region or a nation. Plans are classified into types: Agriculture, Forestry, Fishing, Energy, Industry, Transport, Waste, Water, Telecommunication, Tourism, Urban, and Environmental plans. Each plan defines activities that should be carried out during the plan implementation. Activities are roughly divided into six types: infrastructures and plants, buildings and land use transformations, resource extraction, modifications of hydraulic regime, industrial transformations, and environmental management.

Before any implementation, these plans have to be environmentally assessed, under the strategic environmental assessment (SEA) directive.[1] SEA is a method for incorporating environmental considerations into policies, plans, and programs that is prescribed by European Union policy.

Technology to Support Policy Makers

The regional planning activity can be easily cast as a combinatorial optimization problem. There are a number of technologies supporting decision making and optimization in the policy planning field (Gavanelli et al. 2013), namely constraint programming, mixed integer linear programming, and metaheuristics. They are extremely useful for a number of reasons: First, because they provide a tool that automatically performs planning decisions, taking into consideration the budget allocated on the plan by the regional operative plan, as well as national and EU guidelines. Second, because they can take into consideration environmental aspects during plan construction, avoiding trial-and-error schemes. Third, because they enable the generation of alternative scenarios. Scenario comparison and evaluation also comes for free.

The importance of applying decision support systems to regional planning derives from the huge economic impact that wrong decisions can have. To better understand the amount of money these plans have to manage, let us consider an example: for 2007–2013, the EU structural funds and the cohesion fund, aimed at supporting the regions of Europe and their integration, distribute a total budget of € 347.41 billion. Each European region can take full advantage of several million euros managed and distributed by

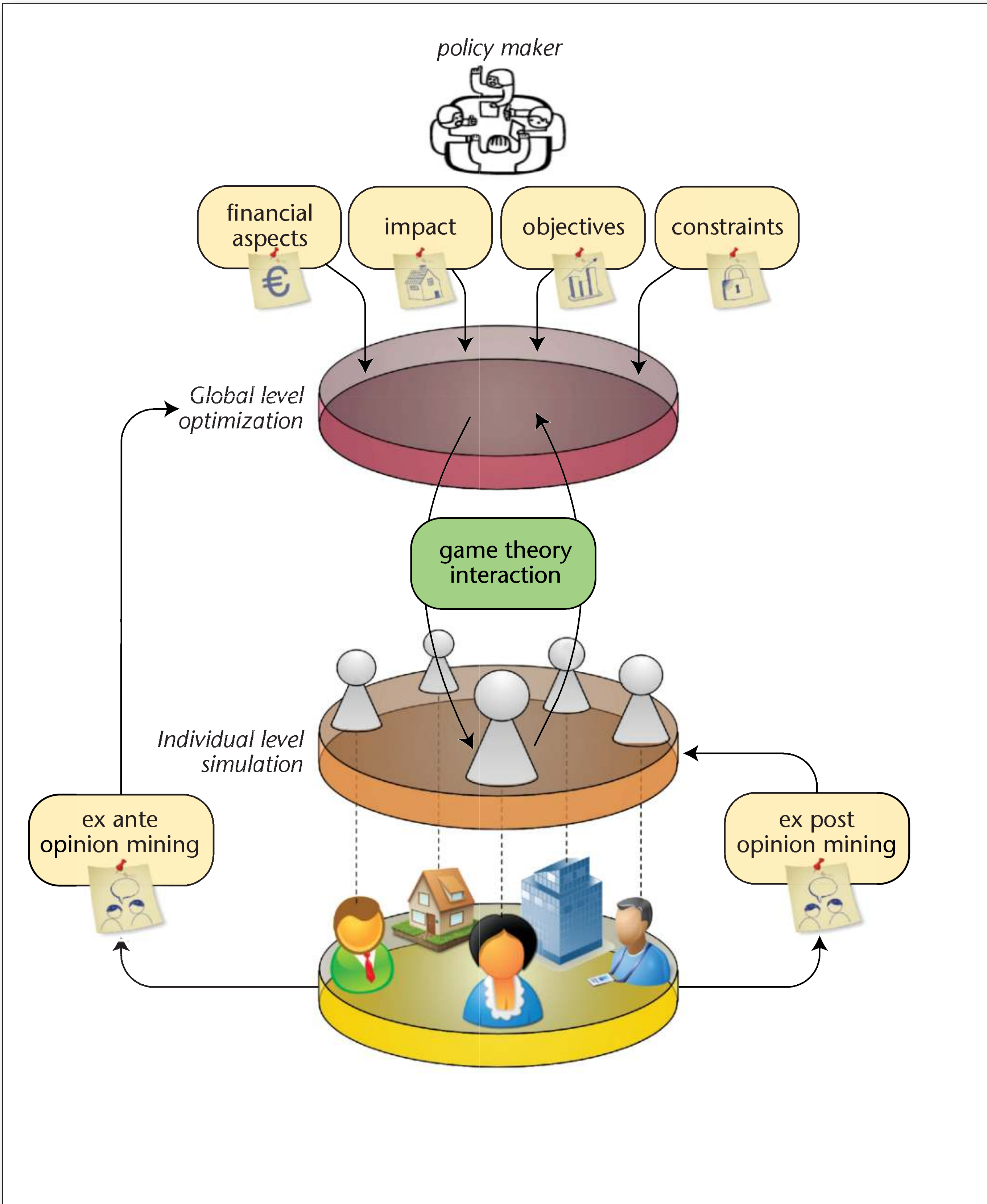

Figure 1. The Structure of the ePolicy Project.

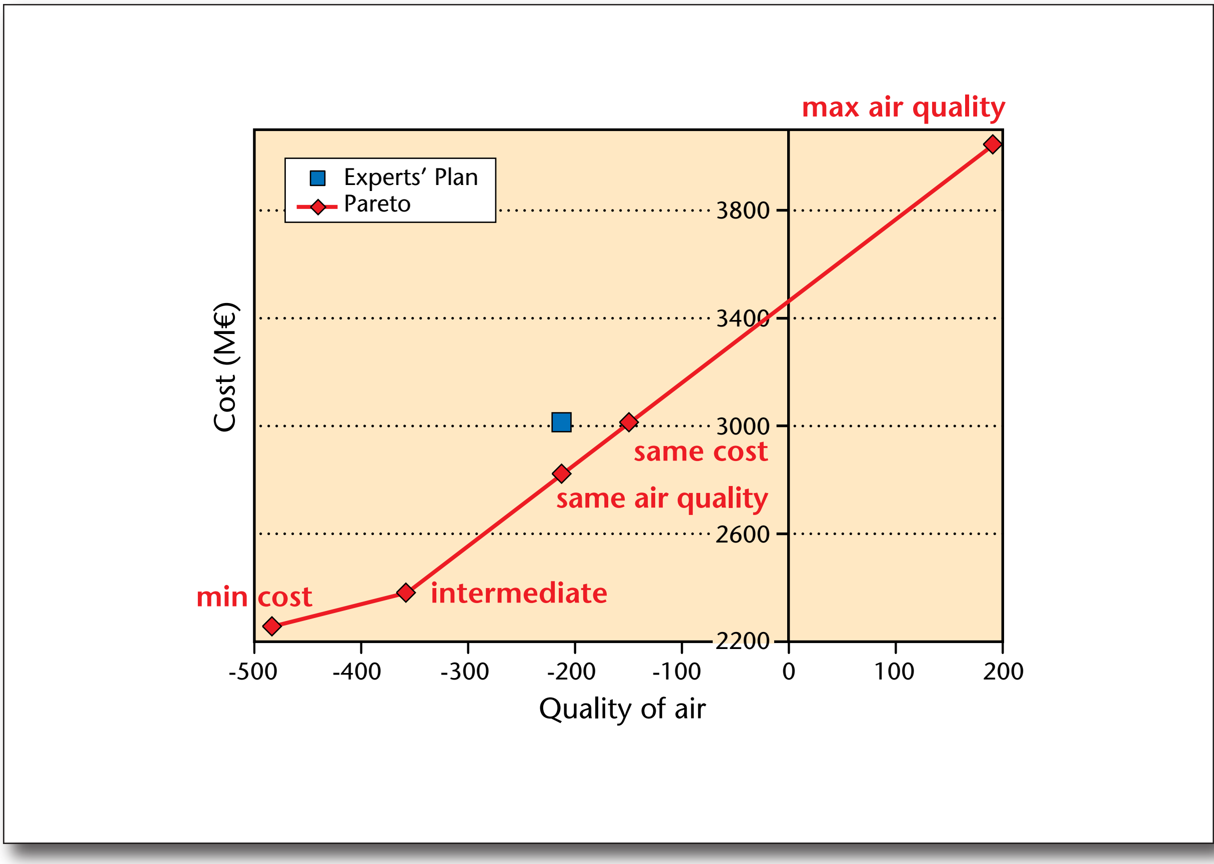

Figure 2. Pareto Frontier of the Quality of Air Against Cost.

an operational program (OP); an OP sets out each region's priorities for delivering the funds. Regional priorities must be consistent with the strategic framework.

An Example on Energy Policies

To design a constraint-based model, we have to define variables, constraints, and objectives. Variables represent decisions to be taken. To each activity we associate a decision variable that defines the magnitude of the activity itself. We distinguish primary and secondary activities: some activities are of primary importance in a given plan. Secondary activities are those supporting the primary activities by providing the needed infrastructures. In case of the energy plan, primary activities are those producing energy, namely renewable and nonrenewable power plants. Secondary activities are those supporting the energy production, such as activities for energy transportations (for example, power lines), and infrastructures (for example, dams, yards).

Primary and secondary activities are of course linked by constraints stating the amount of each secondary activity per unit of primary. In the model we can state constraints limiting the available budget either on the overall plan, or on parts of it. For instance suppose we have already partitioned the budget into chapters; we can impose the budget constraint only on activities related to a given chapter.

The plan outcome could also be constrained. For example for an energy plan, the overall amount of energy produced is an expected outcome. As well, bounds for each activity could be easily imposed meeting EU requirements or national guidelines.

Concerning objective functions, there are a number of possibilities as suggested by planning experts. From an economics perspective, one can decide to minimize the overall cost of the plan, subject to budget constraints. On the other hand, one could maintain a fixed budget and maximize the plan outcome. Finally, the planner could decide to produce a green plan and consider environmental indicators such as the air quality, or the quality of the surface water. The system partitions the budget on activities to obtain a sustainable plan for a given receptor. Clearly, more complex objectives can be pursued, by properly combining the above mentioned aspects. An example is to use a multicriteria objective taking into account for example the cost and the air quality. In this case, we come up with a Pareto optimal frontier. The Pareto frontier of the Emilia-Romagna Regional Energy Plan 2011–2013 is depicted in figure 2.

Strategic Environmental Assessment

The impacts of a policy plan on the environment are evaluated with the so-called strategic environmental assessment (SEA) (Sadler et al. 2010), which relates activities performed in the region to environmental indicators. This assessment procedure is currently performed by environmental experts after a plan has been designed. Taking into account impacts a posteriori enables only corrective interventions that can at most reduce the negative effect of wrong planning decisions.

One of the instruments widely used for assessing a regional plan are coaxial matrices (Cagnoli 2010), which are a development of the network method (Sorensen and Moss 1973). These matrices are defined by environmental experts. One matrix $\mathcal{M}$ defines the dependencies between the activities contained in a plan and positive and negative impacts (also called pressures) on the environment. Each element m^i_j of the matrix $\mathcal{M}$ defines a qualitative dependency between the activity i and the negative or positive impact j. The dependency can be high, medium, low, or null. Examples of negative impacts are energy, water, and land consumption, variation of water flows, water and air pollution, and so on. Examples of positive impacts are reduction of water/air pollution, reduction of greenhouse gas emission, natural resources saving, creation of new ecosystems, and so on.

The second matrix $\mathcal{N}$ defines how the impacts influence environmental receptors. Each element n^i_j of the matrix $\mathcal{N}$ defines a qualitative dependency between the negative or positive impact i and an environmental receptor j. Again the dependency can be high, medium, low, or null. Examples of environmental receptors are the quality of surface water and groundwater, quality of landscapes, energy availability, wildlife wellness, and so on.

As an example, the matrices currently used in Emilia-Romagna, a region of Italy participating to the ePolicy project, contain 93 activities, 29 negative impacts, 19 positive impacts, and 23 receptors and assess 11 types of plans. As far as computational demand is concerned, managing linear constraints is easy (this is clearly an approximation of reality). However, if we consider nonlinear relations between activities and pressures and nonlinear relations between pressures and receptors, the model and its solution would be much more computationally challenging. An example of nonlinear dependency is the one on the landscape. If the landscape has been already compromised by an activity (for example the construction of a big biomass power plant), the addition of another activity would not result in a double negative effect. Basically the effect on the landscape presents a saturation after the first activity that negatively impacts on it.

A number of techniques have been proposed for performing environmental assessment of a given plan, namely probabilistic reasoning (Gavanelli et al. 2010) and fuzzy and multivalued logic (Gavanelli et al. 2011).

However, performing the strategic environmental assessment during the plan construction means combining the evaluation and the planning models. This can be easily done in a constraint-based model as the one presented above.

To compute the environmental impact, we can sum the contributions of all the activities and obtain the estimate of the impact on each environmental pressure. In the same way, given the vector of environmental pressures, one can estimate the influence on the environmental receptor by means of the matrix $\mathcal{N}$, which relates pressures with receptors. We can impose constraints on receptors and pressures. For example, we can say that the greenhouse gas emission (that is a negative pressure) should be constrained by a given threshold.

Merging planning and environmental assessment gives the policy maker the ability to compare different scenarios for what concerns the environmental receptors.

The Regional Energy Plan 2011–2013

We now describe a case study of application of the decision support system. This example is fully described by Gavanelli, Riguzzi, Milano, and Cagnoli (2013) along with the detailed corresponding model. We restrict the example to the regional plan chapter devoted to the electric energy production from renewable energy sources. The considered electric power plants are minihydroelectric plants, photovoltaic plants, thermodynamic solar plants, wind generators, and, again, biomass power plants.

For each energy source, the plan should provide: the installed power, in MW; the total energy produced in a year, in kTOE (TOE stands for ton of oil equivalent); the total cost, in M€. The ratio between installed power and total produced energy is mainly influenced by the availability of the source: while a biomass plant can (at least in theory) produce energy 24/7, the sun is available only during the day, and the wind only occasionally. For unreliable sources an average for the whole year is taken.

The cost of the plant, instead, depends mainly on the installed power: a solar plant has an installation cost that depends on the square meters of installed panels, which in their turn can provide some maximum power (peak power).

Technicians in the region estimated (considering current energy requirements, growth trends, foreseen energy savings) the total energy requirements for 2020; out of this, 20 percent should be provided by renewable sources. Out of this requirement for 2020, they proposed a percentage to be provided

Electrical Power Plants`	Power 2010 (MW	Power 2013 (MW)	Energy 2013 (kTOE)	Investments (M€)
Hydroelectric	300	310	69.3	84
Photovoltaic	230	850	87.7	2170
Thermodyn. Solar	0	10	1	45
Wind Generators	20	80	10.3	120
Biomasses	430	600	361.2	595
Total	980	1850	529.5	3014

Table 1. Energy Plan Developed by the Region's Experts.

Electrical Power Plants	Power 2010 (MW)	Power 2013 (MW)	Energy 2013 (kTOE)	Investments (M€)
Hydroelectric	300	303	67.74	25.2
Photovoltaic	230	782.14	80.7	1932.51
Thermodyn. Solar	0	5	0.5	22.5
Wind Generators	20	140	18.03	240
Biomasses	430	602.23	362.54	602.8
Total	980	1832.37	529.5	2823

Table 2: Energy Plan that Dominates the Experts' Plan, Retaining Same Air Quality but with Lower Cost.

during the plan 2011–2013: about 177 kTOE of electrical energy and 296 kTOE of thermal energy.

Beside assessing the plan proposed by the experts, we also provided new, alternative plans. In particular, we searched for optimal plans, both with respect to the cost, and to the quality of the air. Since we have two objective functions, we plotted the Pareto-optimal frontier. The Pareto frontier is shown in figure 2, together with the experts' plan produced manually.

Figure 2 shows that, although the plan devised by the experts is close to the frontier, it can be improved. In particular, we identified on the frontier two solutions that dominate the experts' plan: one has the same cost, but better air quality, while the other has same air quality, but a lower cost.

Table 1 contains the plan developed by the region's experts, while table 2 shows the plan on the Pareto curve that has the same quality of air as the plan of the experts. Note that with the optimal plan, we can save 191M euros (6.3 percent of the experts' plan cost) and obtain the same air quality. The energy produced by wind generators is almost doubled (as they provide a very convenient ratio (air quality)/cost, we have a slight increase in the cheap biomass energy, while the other energy sources reduce accordingly.

Concerning the environmental assessment, we plot in figure 3 the value of the receptors in significant points of the Pareto front. Each bar represents a single environmental receptor for a specific plan plotted in the Pareto Frontier of figure 2. In this way it is easy to compare how receptors are impacted by different plans.

Implementation

We now describe a case study of application of the decision support system. This example is fully described by Gavanelli, Riguzzi, Milano, and Cagnoli (2013) along with the detailed corresponding model. We restrict the example to the regional plan chapter devoted to the electric energy production from renewable energy sources. The considered electric power plants are minihydroelectric plants, photovoltaic plants, thermodynamic solar plants, wind generators, and, again, biomass power plants.

The integration of a global perspective taking into account regional needs, financial constraints and objectives, and the individual viewpoint would be a real added value of a decision support system. Regional policy decisions foster global objectives. These objectives may include moving in the direction of the Kyoto Protocol aimed at the stabilization of greenhouse gas concentrations in the atmosphere at the level that would prevent dangerous anthropogenic interference with the climate system, or the 20-20-20 initiative aimed at achieving three ambitious targets by 2020 in Europe: reducing by 20 percent its greenhouse gas emissions, having a 20 percent share of the final energy consumption produced

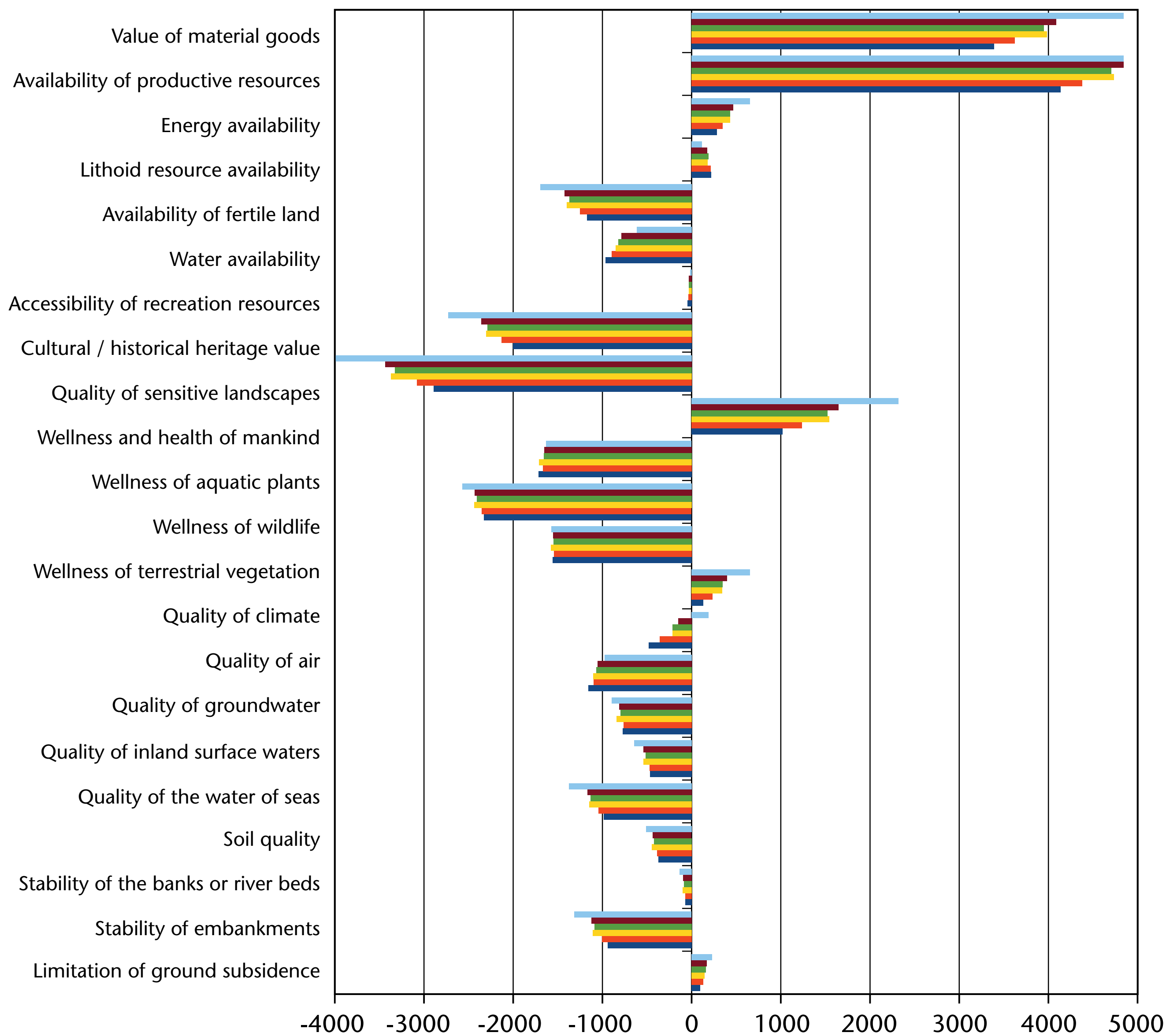

Figure 3. Value of the Receptors on the Pareto Front.

by renewable sources, and improving by 20 percent its energy efficiency. These are clearly global objectives that may not be perceived as a priority by individuals. The smooth interaction of the global and individual levels in a unified and flexible computer-aided tool constitutes a political innovation and could produce a huge impact in terms of optimal resource allocation and land use activities.

In general, after a plan is created and assessed, the policy maker should define actions for the plan implementation. It is often the case, in fact, that goals at the regional level conflict with goals at the subregional level and with individual or business goals. Thus it is not enough merely to define an optimal regional policy goal; in addition there must be implementation through instruments that aim to ensure that actors behave in a way that will lead to the goal. Policy implementation instruments include the following: (1) regulatory instruments: self regulation by voluntary bodies, standards imposed by formal standards bodies, legislation; (2) economic instruments: taxes, fees, and user charges, certificate trading, procurement policies, subsidies; (3) cooperation instruments: voluntary agreements, producer and consumer associations; and (4) information instruments: labelling schemes, reporting requirements, advice services, technology transfer.

Policy makers have a choice of which of these policy instruments to implement, either individually or in combination. Each has advantages and disadvantages, depending on the context, and may have unintended and unforeseen consequences. The selection of the best instruments to achieve a specific goal may be difficult.

Beside understanding which policy instruments are available, the region has also to decide how to distribute the available budget, that is, the mechanism to be adopted. In many regions, for example, incentives are distributed to stakeholders by means of periodical auctions that indeed do not result from a specific strategy, but rather from extemporary actions. In these auctions the bids are ranked on the basis of various criteria (including the cofinancing percentage), and the first n bids that satisfy the budget constraint are funded. This mechanism is not necessarily a truthful one, that is, a mechanism in which agents truthfully report their private information. Therefore, together with the plan, we have to define a proper set of policy instruments, the budget allocated to each of them and a corresponding mechanism to distribute the money. Each solution has a cost and its own impact on the society. Understanding the impact of these instruments is very complex, but essential for devising the proper instrument portfolio that achieves the plan objectives.

There are mainly two core technologies for supporting the implementation step of the policy-making process that can be used either in isolation or as an integrated solution: social simulation and mechanism design. We will briefly discuss the former next, and the latter in the following section in more detail.

Several modeling techniques, often collectively referred to as social simulation, have successfully been used to represent the responses of societies to policy interventions. Agent-based modeling (ABM) (Gilbert 2007) is the most appropriate to represent complex social dynamics because of its capacity to capture interactions and responses in a spatial environment. However, increasingly methods of social simulation are moving towards a common ground, with agent-based modeling incorporating aspects of system dynamics and microsimulation. An agent-based model is a computational method for simulating the actions and interactions of autonomous decision-making entities in a network or system, with the aim of assessing their effects on the system as a whole. Individuals and organizations are represented as agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. Even a simple agent-based model can exhibit complex behaviour patterns because a series of simple interactions between individuals may lead to the emergence of more complex global scale outcomes that could not have been predicted just by aggregating individual agent behaviours.

Social simulation can be used for assessing the social impact of policy instruments and mechanisms. In fact, not only economic aspects affect the agent decision.

As an example consider in figure 4 the trend of incentives provided by the Italian government for three classes of plants (class 1 refers to plants with an installed power less than or equal to 3 kilowatts, class 2 refers to plants whose power is between 3 kilowatts and 20 kilowatts, and class 3 refers to plants whose power is between 20 kilowatts and 200 kilowatts). Figure 5 shows the installed power for the same classes of plants. We can see that there is no correspondence between the trends.

Social aspects (Jager 2006) play an important role such as environmental sensitivity, feeling of belongingness to a group, feeling of freedom from energy providers, importance of creation to agent trust in the government, and future and perceived bureaucracy. These aspects, together with economic and financial considerations can be used to model agents that react to energy policy instruments and mechanisms to come up with a simulated renewable energy diffusion corresponding to instruments and mechanisms.

This component is extremely computationally demanding, needing to simulate a huge number of agents acting, interacting, and making decisions in a complex environment. High-performance computing might be a driver for obtaining realistic and accurate simulations.

Game Theory and Incentive Design for Policy Making

A policy is typically a set of rules that is designed to facilitate the achievement of certain goals or objectives on the part of a country or organization. A policy should aid decision making and should evolve as the objectives change over time. A protocol is more specific than a policy because it defines a set of procedures to be followed for the accomplishment of an identified task. It is well-defined procedure that controls how tasks are achieved.

The adherence to a protocol associated with the

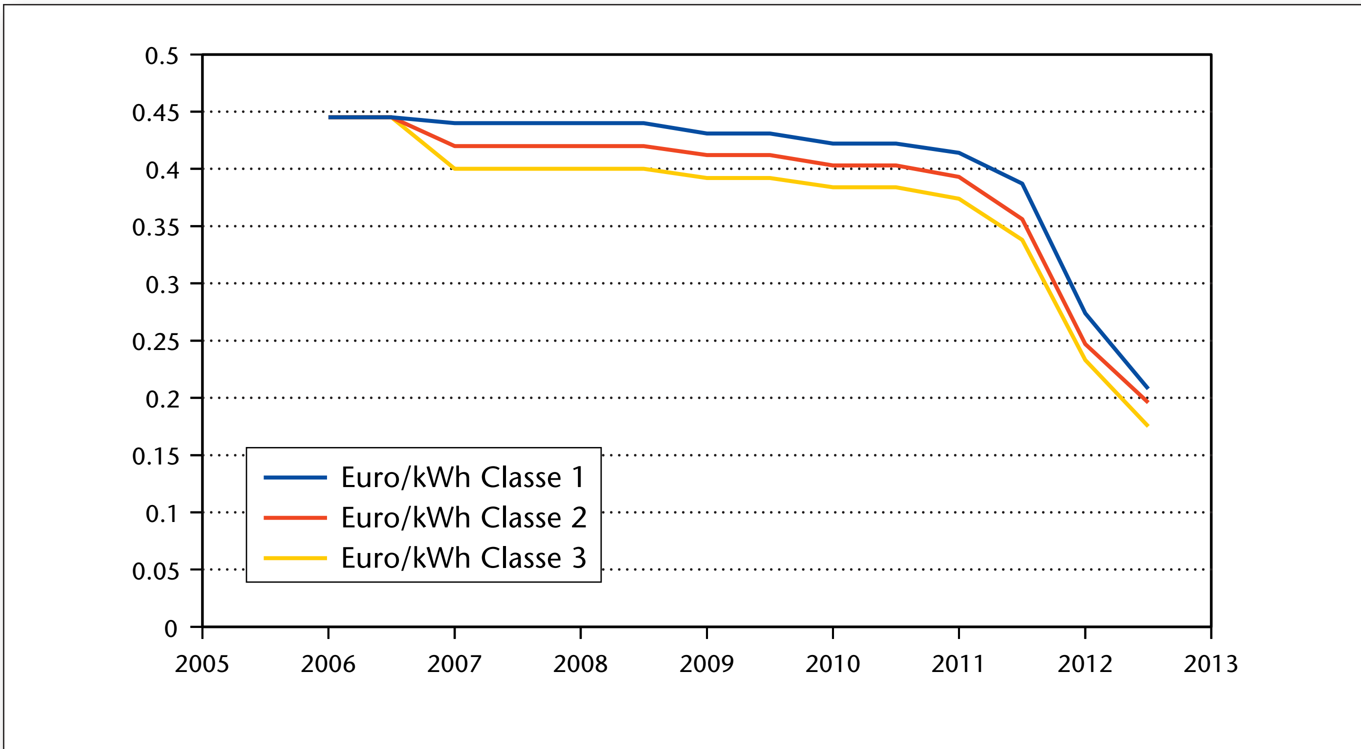

Figure 4. Trend of Italian Incentives to Photo Voltaic.

completion of a task brings clarity and certainty to the state of a task. Protocols tend to be observed repeatedly and can be refined based upon delivery against an overarching policy that itself also changes as an organization's needs evolve. Protocols are often considered to be an effective way to establish standard and repeatable processes for large organizations whose management requires mechanisms for controlling large groups of individuals. Policies and protocols are thus interwoven management tools with strong dependencies.

The game-theoretic analysis of deliberation and negotiation and the normative theory of deliberative democracy both view contention for resources from different perspectives but have developed in mutual isolation. A study by Landa and Meirowitz (2009) confronted the arguments raised by normative theorists opposed to the perceived relevance of underlying assumptions in game-theoretic work. They found that the game-theoretic approach is particularly well suited for providing insights about the feasibility of deliberative institutions and practices. Game theory is improving our understanding of decision making and, in particular, how economic agents react to a set of rules. The central solution concept surrounds an equilibrium in which agents do not have an incentive to unilaterally deviate from a specific action (Nash 1951). Recent research has extended the range of solution concepts to address broader environments that include uncertainty, stochastic dynamics, and other complicating factors. We survey extant work related to game theory as a framework for assessing the efficacy of policies and protocols.

In particular, the field of mechanism design is a branch of economics whose primary application is the design of protocols for the sale or procurement of items. It is particularly relevant to policy making because it concerns the design of protocols for implementing policy objectives in specific settings. The Nobel Prize for economics was awarded to Leonid Hurwicz, Eric Maskin, and Roger Myerson in 2007 for having laid the foundations of mechanism design theory. This brought recognition to the founders of a field that has contributed enormously to policy making and governance.[2] Leonid Hurwicz initiated research in this field in the 1960s when he examined how a planner should reach a decision when the quality of the decision relies on information spread among numerous people. Mechanism design theory formulates this problem mathematically and studies properties of allocation and payment rules. Among Hurwicz's key insights is the idea that the self-interested agents must find it in their interest to reveal private information. This insight informed a contemporary intellectual debate concerning the relative merits of capitalism and socialism. It helped governments understand the importance of incentives and private information and to consider effective regulation of

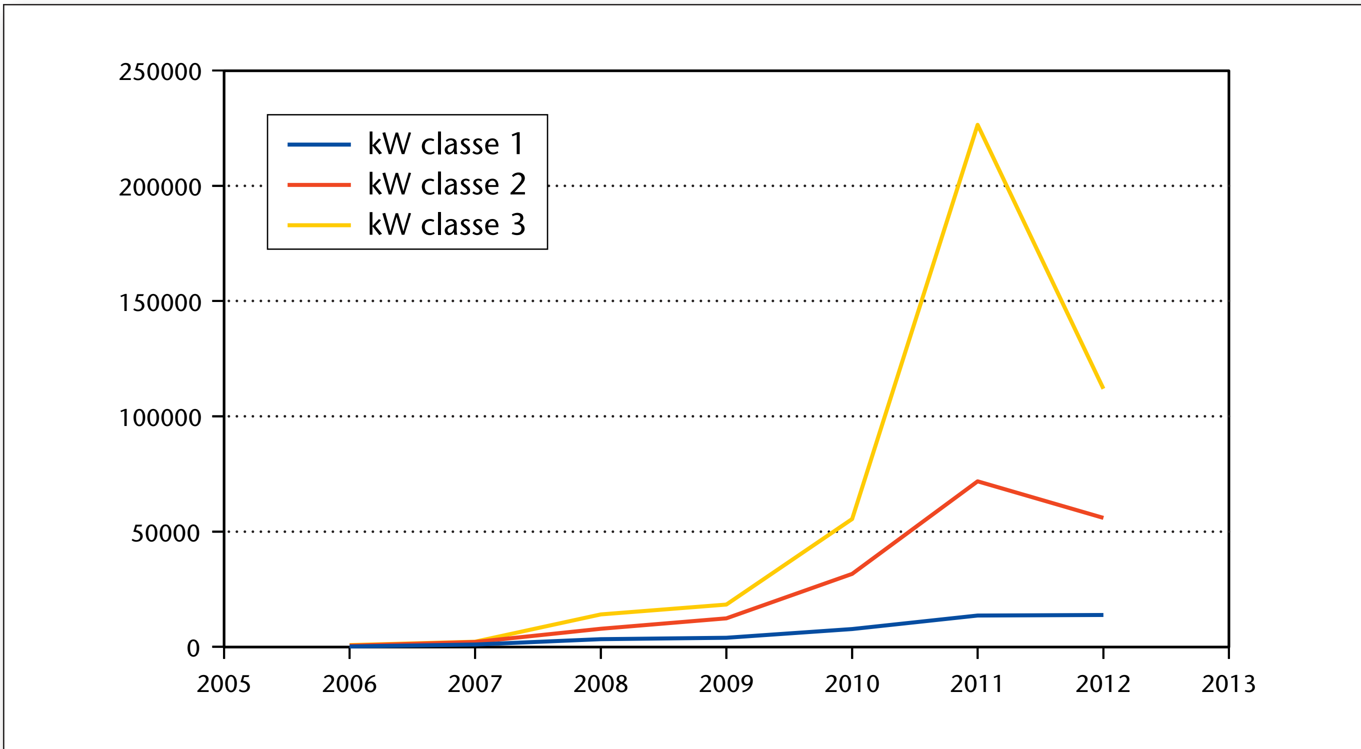

Figure 5. PV Adoption in Emilia Romagna.

capitalist economies (Legros and Cantillon 2007). Key contributions from Maskin and Myerson extended the theory further in the 1970s and 1980s. Mechanism design theory now provides a general framework to study collective decision problems and many specific subfields have been studied. We examine the emergence of mechanism design as a rapidly evolving economic tool that aims to improve the effectiveness of economic protocols given a model of game-theoretic rational decision making by agents.

Game Theory and Policy Making

To design a constraint-based model, we have to define variables, constraints and objectives. Variables represent decisions to be taken. To each activity we associate a decision variable that defines the magnitude of the activity itself. Policy makers frequently make decisions regarding income gathering and expenditure. The most complex challenges for policy makers include tax compliance management and efficient expenditure of funds to support social objectives. We first need to understand the imperatives of the players in a setting ruled by policy makers. We can use game theory to model their actions and reactions in this environment.

Game theory is a mathematical theory of strategic interaction where multiple players must make decisions that may affect the interests of other players. An auction is an example of a game in which bidders are competing agents, each of whom is seeking to maximize his/her utility (Holland 2005). The bid taker sets the rules for the game in such a way as to achieve his/her objective, which is often revenue maximization but may also be the fulfilment of some social objective. The bidders, on the other hand, will strategize so that their expected surplus is maximized (Krishna 2002, Milgrom 1989, Milgrom 2004, Ockenfels and Roth 2002).

A strategic equilibrium is a profile, or combination, of strategies such that if other players conform to the equilibrium strategies (that is, other players are rational), no player has an incentive to unilaterally deviate from his equilibrium strategy.[3] Game theory provides several solution concepts to compute the outcome of a game with self-interested agents. A solution concept is used to predict the strategies agents will choose in order to maximize their utility, thus determining an equilibrium position for the game. These concepts assume knowledge about agent preferences, rationality, and shared information about one other. The best known concept is that of a Nash equilibrium, which states that in equilibrium every agent will select a utility-maximizing strategy given the strategy of every other agent (Nash 1951). A Nash equilibrium is self-referential and constitutes a profile of strategies that form optimal reactions to other agents' optimal reactions. Nash equilibrium is the pure form of the basic concept of strategic equilibrium; as such, it is useful mainly in normal form games with complete information. When allowing for randomized strategies, at least one Nash equilibrium exists in any game with regular payoff functions.[3] A game may possess one or more Nash equilibria.

Modeling Agent Behavior

The behavior of agents often depends upon whether they can accurately predict the actions of other agents. In an independent private-values model, each bidder knows how much he/she values the object for sale but his/her value is not dependent upon the bids of others (Friedman 1956, Vickrey 1961). Each bidder derives a value from only his/her own personal tastes and not external factors such as resale value. The revelation of other agents' types does not influence each agent's private type.

The common-values model was subsequently introduced, where the true actual value is the same for everyone, for example, the oil in a drilling rights auction, but bidders have different private information (signals) about the true actual value (Rothkopf 1969, Wilson 1967, Wilson 1977). In this model a bidder would change his/her estimate of the value if he/she learned another bidder's signal. Common valuations often occur in auctions for rights to natural resources (Capen, Clapp, and Campbell 1971). If a bidder's signal was significantly more than all other bids for example, he/she may reestimate the value of the item, therefore, the bidder's ex-post valuation may be decreased. If it decreases to below his/her bid amount, the bidder is then a victim of the winner's curse, a term first coined by Capen, Clapp, and Campbell (1971). The winners in common-value auctions are necessarily the most optimistic bidders when payment is conducted using a first-price scheme. This can sometimes result in winning an item at a cost of more than the ex-post valuation (Bulow and Klemperer 2002, Krishna 2002, Wilson 1969), which may result in serious losses for the winner (Harstad, Kagel, and Levin 1995).

Environments with asymmetric information describe situations in which some agents hold private information that is relevant to all parties (Wilson 1967). This information can be directly relevant in that it directly affects the payoffs of the bidders. For example, when the bid taker knows the quality of the items for sale but the bidders do not. Asymmetric information can also be indirectly relevant by helping each agent to gauge the expected rational behavior of others and thereby solve his strategic uncertainty.

Mechanism Design

Mechanism design can be considered as inverse game theory whereby the rules of the game are decided by an authority so as to fulfil some objective. Two typical goals of auction design are either revenue maximization or maximization of social welfare. The goal of maximizing revenue is an obvious one and features in auctions where the identity or private valuations of the winning bidder(s) matter little when compared to the revenue received by the bid taker. In some circumstances, however, the bid taker may wish to achieve certain social objectives, but because these individuals' actual preferences are not publicly observable, the analysis of such auctions can become more complicated. The mechanism design problem is to elicit these preferences so that they may be aggregated into social preferences to form a collective decision.

The traditional goal of mechanism design is to determine the rules of a game in which an overall equilibrium (or equilibria) is reached according to some desirable system-wide properties, given that all participating agents are self-interested (Mas-Collel, Whinston, and Green 1995). A social choice function (SCF) describes the properties that the outcome should possess. Some typical desirable properties include the following:

Individual Rationality: No agent attempts to take part in a trade that fails to increase, or at least leaves constant, his/her own utility (Luce and Raiffa 1957). This is an important property if agent participation is voluntary.

Efficiency: The outcome must maximize overall agent utility, thereby maximizing social welfare.

Revenue Maximizing: A single agent, an auctioneer, for example, maximizes his/her revenue (utility).

Budget Balance: The sum of all agent payments equals zero, therefore, no money is extracted or injected into the system. This is particularly important for any self-sustaining mechanism where no external benefactor exists to subsidize the system.

However, these desirable properties may directly conflict with one another. For example, budget balance and efficiency conflict in Vickrey auctions, which achieve only the latter property.

Mechanism Design for Economic Policy Making

Mechanism design theory is ubiquitous and affects almost all aspects of policy with implications at two levels. Firstly, it tells us when markets can be expected to lead to desirable outcomes and whether other institutions should be considered instead. Secondly, mechanism design theory offers useful design guidance for alternative institutions when markets fail. The most conspicuous policy areas that have benefitted from mechanism design are listed next.

Regulatory Economics: In Baron and Myerson's seminal work on regulatory policy making, they used mechanism design to derive optimal regulatory schemes ensuring the provision of public services at least cost (Baron and Myerson 1982). Later research showed that, when cost realizations are observable, simple mechanisms can achieve this objective. Such results have improved actual regulatory schemes and the design of contracts between international institutions.

Auction: Auctions are one of the first and most prominent applications of mechanism design theory. They benefitted greatly from Nobel Prize winners Maskin and Myerson's contributions regarding the challenge of how to allocate some item(s) among bidders when the value of the item(s) to a bidder is private (known only to that bidder). The objective of the auction designer may be to maximize revenue, or to ensure that the items are awarded to those who value them the most thus maximizing economic efficiency. Governments use auctions to allocate a country's natural resources that include mineral deposits, exploration rights, timber, frequency spectrum or property. Governments also use reverse auctions to procure goods and services from private sector suppliers. Mechanism design theory has been instrumental when guiding the design of a set allocation and payment rules for auctions across many applications.

Environmental Policy: Global coordination of pollution control is essential given that we all share a single atmosphere and ocean system. Mechanisms for internalizing the externalities of pollutants such as carbon dioxide form an integral aspect to any solution that will curtail pollution. Economic theory has informed efforts such as the Kyoto Protocol but more effort is required in order to overcome political hurdles. In related applications, mechanism design theory also informs the design of sustainable management of natural resources such as fishing or tree-felling.

Development Programs: Mechanism design theory has also heavily influenced the design of aid programs in poor countries (Rashid, Shorish, and Sobh 2006). Traditional solutions to community problems such as lending, land sharing arrangements and resource management have been improved following the contributions of mechanism design theory (Legros and Cantillon 2007). For example, mechanism design helps evaluate the relative performance of different cross-reporting and joint liability in microfinance arrangements (Karim 2009).

Public Participation in Policy Issues

Social participation is a key aspect for a democratic process. For this reason, a number of e-Participation tools have been developed and are currently used to enable public consultations. Clearly, citizen participation in the definition of public policies might be fostered by the use of mobile services, such as visualization of big amount of data in an intuitive way or the possibility of customizing the participation actions only in some contexts.

Another way to use opinions from citizens without the need of their direct involvement is to use opinion mining (Pang and Lee 2008) on data extracted from public blogs, forums, and the press. Social networks could also play a fundamental role to understand not only opinions, but also arguments (Gabbriellini and Torroni 2012) supporting them. People opinions might represent an extremely important information for policy makers and might influence not only the planning process, but also the implementation instruments and mechanisms.

Extracting the opinion in a text document based on a vector of features derived from a document corresponds to the modeling task in a standard data analysis framework. Depending on the type of data we have available for this task, different techniques may be applicable to achieve this goal.

Supervised learning is a technique that takes (manually) labeled data constituting the training set, and produces a model that can be seen as an approximation of the unknown function that maps the values of the variables into labels. This type of models can be used to assign labels to new unlabelled samples.

The main issue with this technique is the need of a large amount of training data which should be analysed and tagged by a human expert. Depending on the way we represent opinions (for example, positive vs. negative or an ordered score), different learning algorithms may be applied such as support vector machines, naive Bayes, and decision trees to name a few. Unsupervised learning is a technique that tries to find hidden structure in unlabelled data. In the context of text mining this would correspond to not having training data. The task of this technique is then to cluster texts that share similar feature values that in principles correspond to similar opinions. Typical approaches to unsupervised learning include clustering (for example, *K*-means) and blind signal separation using feature extraction techniques for dimensionality reduction (for example, principal component analysis). Semisupervised learning is a mixture of both previous techniques and it is particularly used approach when the labeled data is scarce. In the model training process, the unlabelled data is taken into account and used to train the model.

On the other hand, we have also semantic approaches to opinion mining (Ding, Liu, and Yu 2008), using natural language-processing techniques to understand the text and extract opinions. In this case, a text is parsed and the meaning of each word is extracted depending on the context. Clearly, understanding an opinion contained in a text is far more complicated that simply understanding the text, but basically it relies on the same techniques.

Conclusion

In this article we have identified a number of techniques that can be effectively used to create support tools for policy makers. While existing AI techniques are mature for being applied in such a field, the authors of this article believe that much effort still needs to be put into their adaptation to the policy-making field and into their integration to provide unified tools. User acceptance is an important aspect to be considered as policy makers hardly trust ICT tools that have been designed by people that do not have any expertise in the policy domain. For this reason the systems should be design in close contact with the policy makers and the validation phase should deeply involve policy makers, planners, and stakeholders.

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Notes

1. See ec.europa.eu/environment/eia/sea-legalcontext.htm

2. See P. Legros and E. Cantillon, The Nobel Prize: What Is Mechanism Design and Why Does It Matter for Policy-Making? (voxeu.org/article/nobel-prize-what-mechanism-design-and-why-does-it-matter).

3. See Sonderforschungsbereich 504, www.sfb504.uni-mannheim.de/glossary.

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