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Towards Proactive and Flexible Agent-Based Generation of Policy Packages for Active Transportation

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Abstract

One of the approaches gaining ground in policy design is the implementation of combinations of policy measures as policy packages with the aim of increasing efficiency and effectiveness of the designed policies. In this paper, we describe the recent advancements in the developments of a virtual environment for the exploration and analysis of policy packages. The virtual environment uses an agent-based modelling approach for the generation of different configurations of policy measures in the policy packages. The benefit of using the approach is the proactive and flexible generation of policy packages as the agents can react to the changes that occur and create packages that are more robust. The system allows faster examination of more alternatives, further exploration of the design space, and testing the effects of changes and uncertainties while formulating policies. The results demonstrate the benefit of using agent-based modelling approaches in the design of complex policies.

1. Introduction

It is generally recognised that effective policies consist of a combination of reinforcing policy measures rather than a single policy tool [1]. And so, to design a policy, a policy maker has to decide which set of policy measures should be selected taking into account that policies are temporally, geographically and culturally specific.

The solution to this problem is open-ended, as alternative policies are not equivalent in their implementation costs, effectiveness and public acceptance. In fact, these important characteristics are a function of the interactions between policy measures and their intrinsic properties. The problem is further complicated by the fact that the solution space is very large, as there may be a large number of policy measures available for each policy goal (often above 100), resulting in an enormous number of possible combinations. The formulation of policies is currently a manual and labour intensive task. This paper introduces a systematic, proactive and flexible approach to the generation of policy packages and describes an agent-based implementation that embodies the approach. The method has the potential to accelerate the policy formulation process and improve the effectiveness of the resulting policies. The contributions of the work presented for formulation of policies are: (a) consideration of a larger portion of the design space because of automation of parts of the overall tasks instead of the traditional manual approaches in policy making; (b) increased choice of alternative packages with varying pros and cons (c) increased likelihood of reaching a better solution through generation of more alternatives and use of representation and evaluation approaches; and (d) development of the equivalent of an "experimental lab" for policy makers to test and explore alternative policy packages and test the effects of changes and uncertainties while formulating policies.

The background information is discussed in Section 2. Section 3 describes the architecture, objectives and conceptual framework used in the modelling approach and Section 4 illustrates its implementation. The results achieved are presented in Section 5 and conclusions and future work are described in Section 6.

2. Background

2.1 Policy Packaging

In this paper we adopt Pohl's [2] definition of policy as "a principle or guideline for action in a specific context" and the task in which the components of a policy are selected and the overall policy is formulated is defined as policy design. In the process of policy design the challenge faced by policy makers is no longer a lack of understanding about possible solutions nor a lack of options to implement, instead, given the complexity of the problems faced, the challenge is how to analyze and explore a large number of complex options, and arrive at the best solutions given time, geographical, budgetary and a myriad of other constraints [3].

Research has shown that capturing and processing large amounts of information is difficult for the human mind and excessive amounts of information can cause inertia and result in consideration of very few options [4, 5]. We believe that using a systematic approach and having access to decision aid tools can facilitate the identification of more suitable options and aid in addressing some of these problems. Furthermore, it is recognized that silver bullets do not exist in policy making and to ensure successful and efficient attainment of the given policy objectives, a combination of policies needs to be implemented [6, 7]. Givoni et al. [8] use the term 'policy package' for this combination of policy measures and define policy packages as "a combination of individual policy measures, aimed at addressing one or more policy goals; a package is created in order to improve the impacts of the individual policy measures, minimize possible negative side effects, and/or facilitate the interventions' implementation and acceptability". Therefore, policy packaging reinforces the need for the consideration of the combination of a large number of options (eg. understanding the potential effectiveness and efficiency of each policy measure, and in combination with other policy measures within a policy package) which further exacerbates the problems faced in policy making.

Previously we have developed a six-step framework [9] that allows a systematic approach to the synthesis and configuration of policies. Based on the six-step framework the Policy Measure Analysis and Ranking Methodology [3] was developed to enable quantitative comparison of the policy measures and to assist in their analysis and selection for implementation by relying on the application of network theory and multiple criteria decision analysis approaches. The aim of our approach has been to simplify the analysis through visualization and ranking methodologies while allowing the policy-makers to systematically consider a large number of policy measures in dealing with a specific policy problem while taking into account additional information (e.g. relations between measures and implementation challenges), going beyond the traditionally considered information.

The framework and methodologies developed for the analysis and ranking of policy measures for the formulation of policy packages were applied to two case studies with domain experts exploring a much larger portion of the decision space than normally considered. The case studies aimed to reduce emissions from the UK transport sector (123 policy measures – see [10]) and to promote active transportation in cities (38 policy measures – see [3, 21])[1].

2.2 Policy Measure Relations

An innovative aspect of the research was the definition and classification of five types of relations between policy measures (precondition, facilitation, synergy, potential contradiction and contradiction – see [3]). Once a library of policy measures has been developed, the next step is to identify these relations among policy measures with the goal of using them for assessment and/or the selection of policy measures. The classification of the policy measure relations is carried out by the domain experts. For a network of n nodes, the relations are stored in an n by n adjacency matrix where each element of the matrix represents a relation between the corresponding row and column nodes[2]. In our experience using a collective decision making procedure for identifying the relations is advantageous and is likely to increase the robustness of the analysis. This is due to the fact that often complex relations exist between the policy measures and clearly distinguishing the relation type at times can be difficult. An iterative approach was used in order to identify inconsistencies and errors where at least one iteration was performed for the identification of each type of relation [3][3]. Visualization of the policy measure relations serve as a final check on the integrity and validity of the identified relations and also help in better grasping the complex relations between policy measures and extracting information that might have been disregarded.

3. Methodology

3.1. Agent-Based Modelling (ABM) for Policy Packaging

Agent-Based Modelling (ABM) is a computational methodology that enables a researcher to create, analyze and experiment with models that are composed of agents that interact within an environment [11]. In ABM complex actions of the agents and their reactions to

[1] Active transportation is the transport of people and/or goods using human muscle power, mainly referring to cycling and walking.

[2] An edge exists between two nodes a and b if element (a,b) of the matrix is equal to 1, and there is no edge between a and b if element (a,b) is equal to 0.

[3] In this study, the policy measure relations are not weighted. It is possible to differentiate between the quality of the relation between policy measures using a weighted network. However, the extent to which a relationship can be quantified is questionable. Nevertheless, if experts are confident in the assessments of policy measure relations or there are models that could provide estimations, such information can be considered in the analysis.

other agents and the environment enables the observation of the outcomes and system effects of a set given set of parameters [12]. Observation of the system effects and their anticipation prior to the implementation of policies has the potential of increasing the chance of successful decision making. Furthermore, ABM systems are scalable and modular [13] and are well-suited for exploring dynamics and complex structures and their characteristics [14] which are all desirable features and relevant for the formulation of policies in complex socio-technical systems.

Virtual environments have been used for the analysis and improved understanding of complex systems in different domains such as energy [15], health [16], food [17], transport [18] or markets [19]. For instance, in case of markets, developing such virtual laboratories enables testing of different regulatory and market structures, e.g. the Electricity Markets Complex Adaptive Systems (EMCAS) model, developed by Argonne National Laboratory [19]. Aside from features that are traditionally considered as positive features of ABM systems (see [12] and [20]), the ABM approach provides the flexibility to deal with different types of data which is useful when a large amount of qualitative data is present and quantification is not possible or is questionable.

We have previously used the framework and methodologies in the development of an ABM decision support system to act as a virtual environment for the exploration and analysis of different combinations of policy measures to build and assess policy packages. The agent-based approach utilized information about policy measure interactions along with internal properties of the policy measures, and user preferences for the analysis and formulation of policies. Furthermore, the ABM system facilitates carrying out tests to observe the effects of changes and uncertainties to policy packages. Similar to the framework and methodologies developed, the decision support system is generic in nature and has been designed with reusability and flexibility considerations in mind for different targets, sectors and geographical scopes.

We are interested in further exploring and tackling the technical complexities of policy formulation by using a computational framework. The focus of this paper is on the enhancement of the system and addressing some of the limitations we had previously identified. Previously we had only considered a single type of a goal (e.g. transport emission reduction) but now we are considering multiple goals and the trade-offs between them. Moreover, we were assuming that the data provided to the system was based on consensus (which was the case in the case studies conducted before) but now are considering different stakeholders and possibility of reaching consensus among them in selection of policy packages from a computational perspective, i.e. how minimal change of weights might allow reaching higher level of consensus.[4]. These enhancements are particularly interesting in policy packaging due to the qualitative/fuzzy nature of problems and consequently the criteria and weights used in assessment. We believe these enhancements will further allow us to better understand and analyze data, and thus increase the level of 'knowledge utilization' in the policy process [22].

3.2 Conceptual Framework

The two main types of agents that operate in the system are the Policy Packer agents and the Assessor agents. Policy Packer agents undertake the selection of policy measures and create the policy packages. Assessor agents evaluate the created policy packages based on their assessment criteria, rank the policy packages, select their preferred package(s), examine other Assessors choices, and explore if they can reach a consensus through negotiation, and provide real-time feedback to other agents and users (through a graphical user interface (GUI)) to help them in their decision making process. Figure 1 illustrates a conceptual ABM framework for the formulation of policies.

3.3 System Architecture and Implementation Environment

The Java programming language [23] has been chosen for the development because of its characteristics of platform independence, automatic memory management and access to an extensive library of freely available code and software (which are used for data retrieval, visualizations, and analysis). Analyses performed on the network of relations among policy measures are outputted to Excel files, which are, in turn, imported by the agent-based toolkit. The agent-based toolkit used for the analysis is Repast Simphony (Recursive Porous Agent Simulation Toolkit [24]). Mathematica is used for computation [25] and to access the discrete mathematics package Combinatorica [26]. The information acquired through user input and Mathematica analysis is channeled back towards Repast Simphony. Figure 2 is a screenshot of the implemented ABM system generating and assessing alternative packages based on the described system architecture.

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[4] We acknowledge the use of agent architectures such as BDI and PECS [27-29] in exploring or simulating human behavior for decision-making. They are relevant from a social science perspective but they are not the focus of this research.

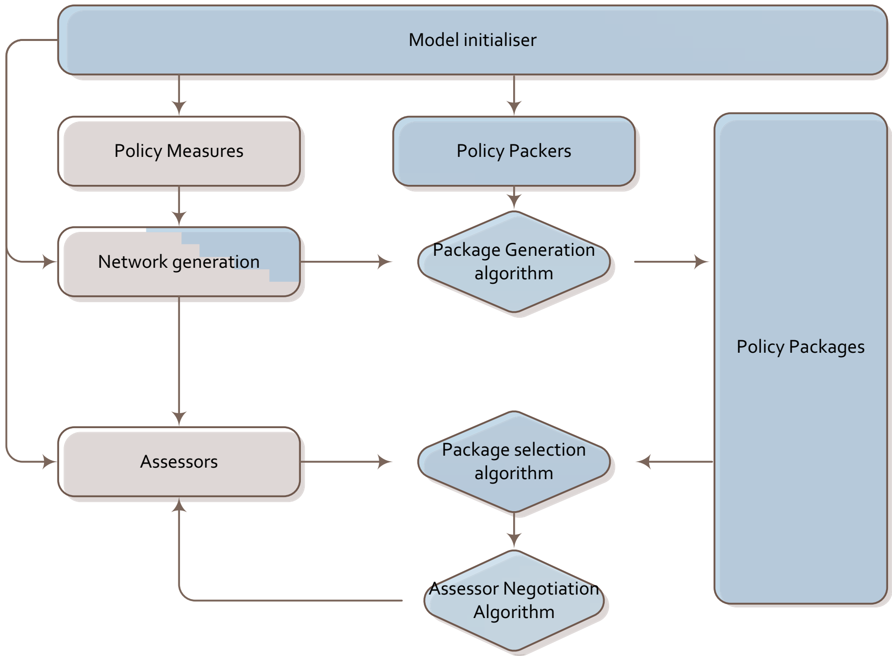

Figure 1 Conceptual framework of the ABM system

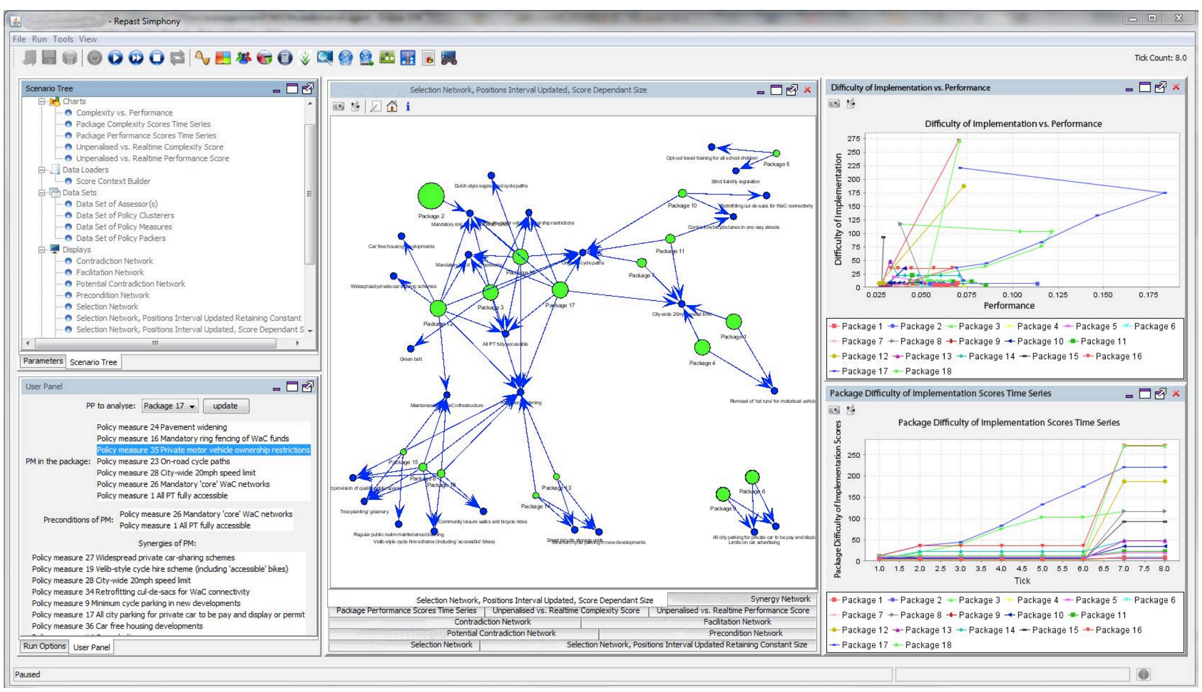

Figure 2 Screenshot of the system generating a large number of policy packages [21].

4. Application of the ABM Policy Packaging System

To illustrate the benefits provided by the ABM system for policy packaging this section briefly describes the implementation of our approach on a case study for promotion of active transportation. The system uses real data and is based on extensive collaboration with domain experts. Section 4.1 gives an overview of the case study and Section 4.2 highlights the input data used from the case study and the initialization process. Section 4.3 details the policy measure selection process for the creation of policy packages. Section 4.4 illustrates the policy package assessment and selection procedures and Section 4.5 details visualizations of the graphical user interface. Subsequently Sections 5.1 to 5.3 further illustrate various functions of the system

4.1 Implementation of the system in active transportation policy

Transport policy is often complex in nature as it entails addressing behavioral and technical aspects which are related. In order to have sustainable transportation, it is important to improve the balance between benefits and the costs of society's mobility needs [30] and a major objective is to increase the level of active transportation (see [31] and [32]). The increase in level of active transportation can be substantial; however, in a majority of countries the level of active transportation has been declining (e.g. DfT [33]). The "Visions of the role of walking and cycling in 2030" research project [34] seeks to develop and evaluate alternatives to change the situation in the UK where active transportation represent 26% of trips in urban areas in 2010 and aims to be increased to 70% by 2030. Following the recent consensus on policy packaging, the Visions project understood that a combination of policy measures into policy packages is needed to support the shift from motorized to non-motorized transportation [34].

4.2 Input Data and Initialization Process

Thirty-eight policy measures that promote active transportation constitute the core of the library of policy measures used in this study (see [21] for the list of policy measures). The repository was created from the Visions 2030 project [34] through participation of domain experts and the use of scientific literature. Properties considered for the policy measures are Cost, Effectiveness, Timescale of Implementation, Delay, Timescale of Effect, Technical Complexity, Public Unacceptability and Institutional Complexity. Five types of interactions between the policy measures were identified (see Section 2.2) and were stored and later retrieved during the initialization phase of the system to form network structures.

The Repast Simphony's runtime agent editor provides a range of basic facilities that includes [24]:

(a) Creation, cloning and deletion of different types of agents during runtime.

(b) Provision of the lists and visualization of agents, their connections and properties.

(c) Creation, Selection and Deletion of the agents and change of their properties and/or links in different networks during runtime.

(d) Provision of the ability to take snapshots or videos of the simulation run.

When the simulation run starts, the following initialization tasks are performed to create the virtual environment for policy packaging in the ABM system:

- Generation of the different agents and data layers (policy packers, assessors, policy measures, etc.), and retrieval and assignment of their properties[5].
- Generation and setup of the custom graphical user interface.
- Acquisition of global parameters and run specific data parameters for the system using data files and through the GUI.
- Generation of the various networks that represent the complex interaction among policy measures and/or agents in the system and definition of the structural relation between different agents and networks in the system[6].

4.3 Selection of Policy Measures

Policy Packer agents undertake the task of generating policy packages by selecting policy measures using global parameters and/or user inputs. Due to space limitations we only highlight the high-level details of the overall decision process of the Policy Packer agents in each simulation run rather than providing the detailed algorithm for each iteration. Each Policy Packer agent starts with a top policy measure, which is either assigned randomly or selected on the basis of its performance calculated through a policy measure ranking methodology [3] based on criteria set by the user.

Initially each Policy Packer agent analyzes the selected policy measure to see if it has any precondition requirements. In case such preconditions exist, those policy measures are added to the package to ensure successful implementation. In the next step, the Policy Packer agent identifies the policy measure that has the highest level of positive interactions (synergy, facilitation, or other user set criteria) with the policy measures in the package. Similar to the previous step, before adding the selected measure to the package the preconditions of the policy measure under consideration are checked. In the case when precondition relations exist, the Policy Packer agent decides whether the new policy measure and its preconditions should be added to the package or not given the package size, cost, time, contradictions with measures already in the package or other constraints,. The process (with a variety of options available to the user) can continue in successive iterations to expand the size of the packages, allowing the user to

[5] Retrieval of the policy measure properties and interaction data was carried out using the JExcel Java library [35].

[6] Network projections, are created using the Jung Network/Graph Library [36].

experiment with different configurations and observe the effects on the performance of the packages.

Each policy packer agent performs an internal assessment and updates the properties of the policy package it has generated at the end of each iteration step based on the policy measures it contains and the analysis step it is performing. Throughout the Policy Packer agent's decision process certain tasks are performed when a specific condition is reached. For instance, initially all of the Policy Packer agents conduct precondition checks. Once all of the agents have carried out their precondition analyses then a change of state must be triggered to allow them to conduct other aspects of analysis (e.g. addition of additional policy measures to the package or checking for constraints such as time, cost or contradictions). Moreover, this information is used by the Assessor agents for the comparison and selection of policy packages and is provided to the user through the GUI.

The ABM system allows the utilization of user inputs during runtime through the Repast ABM toolkit GUI and the custom user panel for addition of new agents, confirmation of their decisions in the user interaction mode (see more in Section 4.5), analysis of the package's content or change of different properties associated with packages or policy measures.

4.4 Assessment and Selection of Policy Packages

Assessor agents allow the consideration of multiple and concurrent stakeholders involved in the policy formulation process that might have single or multiple competing goals. Furthermore, by considering different stakeholders, the possibility of reaching consensus among them in the selection of policy packages can be explored from a computational perspective. Moreover, the stakeholders' priorities can be highlighted on the ranking and development of policies and trade-offs between different goals.

Each Assessor agent evaluates the alternative policy packages based on its own criteria. This helps with identifying more promising packages given a specific set of criteria that each Assessor agent uses. For instance, one Assessor agent might assess the policy packages based on set of criteria that relate to package performance (e.g. time required for implementation, duration of effect), difficulty of implementation (e.g. public unacceptability, institutional complexity), or stability (e.g. level of risk and uncertainty involved).

The Assessor agents' ranking is based on the weighted summation of the scores of the policy measures. All of the criteria in each set associated with an Assessor agent are assigned positive weights fixed to a sum of 1.0. Criteria within each set fall into one of two categories: desirable or undesirable. A criterion is desirable when a high score is considered better, and is undesirable when a lower score is considered better (e.g. Cost, Institutional Complexity). When a mix of desirable and undesirable criteria are present, all the scores are transformed to desirable by using the reciprocal of the values associated with undesirable criteria [37]. The resulting scores are normalized, multiplied by their corresponding weight and summed up to calculate the overall score.

Figure 3 illustrates the Assessor Agent's simplified iteration step algorithm. In each iteration step the Assessor agents find all of the available policy packages and retrieve their information. Based on their goals and criteria they rank all of the policy packages based on their scores and select the highest ranking one. If the negotiation feature is activated the agents will perform their negotiation subprocess as well and finally communicate their ranking score and selection choices in real-time back to the user through the GUI and record them in the log files.

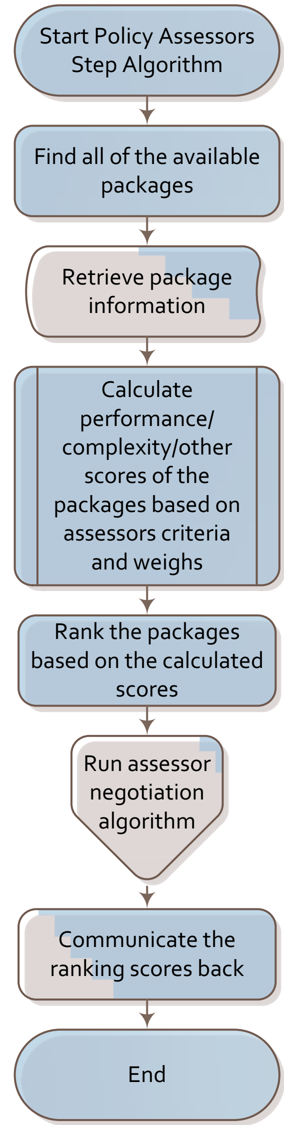

Figure 3 Assessor agents' simplified iteration step algorithm

Figure 4 depicts the Assessor agent's simplified negotiation subprocess. Once the negotiation subprocess is activated (after all of the Assessor agents have selected their initial choice), each Assessor agent will retrieve other Assessors' selection choices and calculate how many other agents have selected a similar policy package as their first choice. If this number is within an acceptable range (e.g. more than 50% of the agents have also chosen the same package), Assessors will keep their original choice and record and report back their selection. In case a consensus cannot be reached using the first choice, Assessor agents will switch to their second choice (and can continue to do so within an acceptable range, for instance changing up to choices that are within 15% of the original score of the first choice) and check whether switching their selected policy package resulted in higher level of consensus. In this case the Assessors will retain the choice and if not, they will revert back to their original choice.

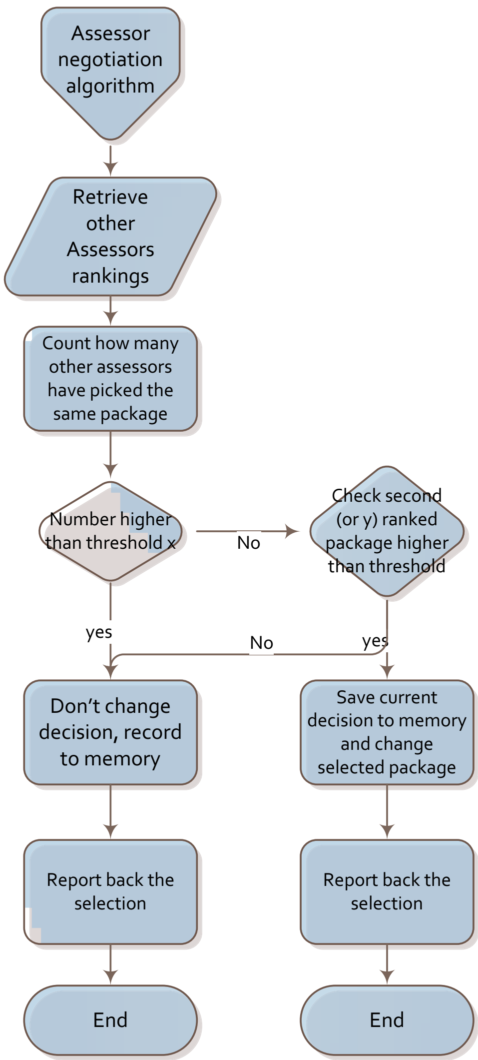

Figure 4 Assessor Agents' simplified negotiation subprocess

4.5 The Role of Visualizations and the Graphical User Interface

Due to the complexity of policy packaging, it is important to provide visualizations of the policy measure networks, the created policy packages with the policy measures they contain, and the performance of different agents with respect to the various criteria that Assessor agent's use. By using the data logged at each iteration step we show various charts depicting the evolution of the properties of the policy packages during the formulation process.

Providing the users the ability to conveniently change the assumptions and data during runtime, to interact with the system and to override the parameters as they see fit is crucial to build trust and create transparency when dealing with complex problems. Therefore, the ABM system has an interactive mode in which agents rely on the user input for crucial decisions such as deactivating a policy package or penalizing its score because of the presence of contradictions within the policy measures it contains. Moreover, aside from the features that Repast Simphony provides, a custom user panel is developed that provides detailed information about individual packages and the policy measures they contain.

5. Results

5.1 An Agent-Based Virtual Environment for Policy Packaging

The developed virtual environment provides the ability to explore and analyze different configurations of policy measures to form policy packages. The output of the virtual environment are the formulated policy packages and the ability to analyze their performance given different stakeholders views and assessment criteria against single or multiple goals.

In our previous work we have showcased and /or developed the following features and applications and try to minimize their repetition here (for detailed explanation of these features refer to [21]):

- Sample policy packages and their analyses: in figure 5 we show a sample policy package developed for promotion of active transportation. The green circle represents a policy package and

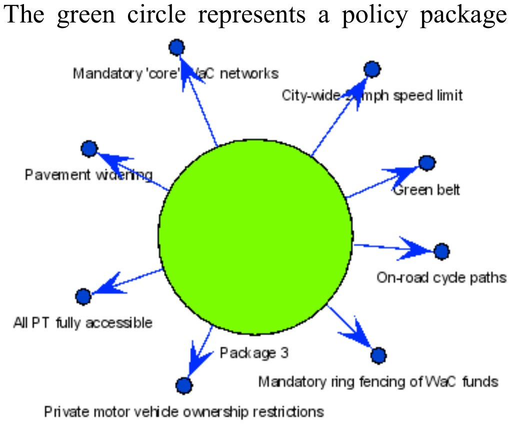

Figure 5 A sample Policy Package

the blue circles connected to it represent the policy measures that have been selected to build the package. The size of the green package in the system represents the score of the policy package based on the assessment criteria selected.

- In policy packaging often very few packages are considered and developed. The use of the system allows for exploration and analysis of a larger number of options in parallel and at no extra cost.
- Custom user panel: A custom user panel was developed to provide additional information about policy packages and full details of the policy measures within a package and their relations with other policy measures.
- Interactive mode: Some of the crucial evaluations of the agents during runtime include checking the policy packages cost, time required for implementation and the existence of contradictions or potential contradictions within a package. In the interactive mode, instead of relying on global parameters provided by the user, the system relies on the user judgment. For instance in the case of notifying the user, rejecting the addition of a policy measure to a package or penalizing the score of a policy package.

5.2 Policy Package Assessments

Assessor agents assess the performance of the policy packages at each iteration step. Figure 6 presents the evolution of the scores of ten policy packages over five iterations based on the criteria of four Assessor agents. In each chart, the x-axis shows the iteration steps and the y-axis represent the score that a specific Assessor has assigned to the packages based on its criteria. It can be seen that, different policy packages will be chosen by different Assessors and in two instances one package has a superior performance to other packages (chart a and b of figure 6). We are currently working on the implementation of the negotiation algorithm that was presented in Section 4. In cases when the top policy packages have similar scores (charts c and d) the algorithm will help in reaching consensus and to better understand the effect of choices by the Assessor agents and whether a slight change in score, due to uncertainties in the assessment criteria and the qualitative nature of the answers, can result in reaching consensus or not.

5.3 Real-time Feedback

One of the benefits of using a virtual environment for policy packaging is the provision of realtime information to the user. For instance, in figure 7 (left) the size of the policy packages have been scaled based on their score under the assessment criteria and weights used. These weights can be changed during runtime. In the next iteration step after a change of weights, the Assessor agents carry out the comparison among packages, re-evaluate their package scores and various visualizations are updated. By coupling the ranking methodology, the selection algorithm and the visualization of the results, it has become possible for the user to observe immediately the effects of a change in the input parameters on the system (in this instance the criteria weights). Package 2 (which only contains one policy measure) has a similar score to package 3 (with a much larger number of policy measures) when 40% of the total weight is allocated to cost (favorable to small packages with low costs, such as package 2). However, when cost only accounts for 20% of the total score, package 2 is not that attractive (figure 7 (right)).

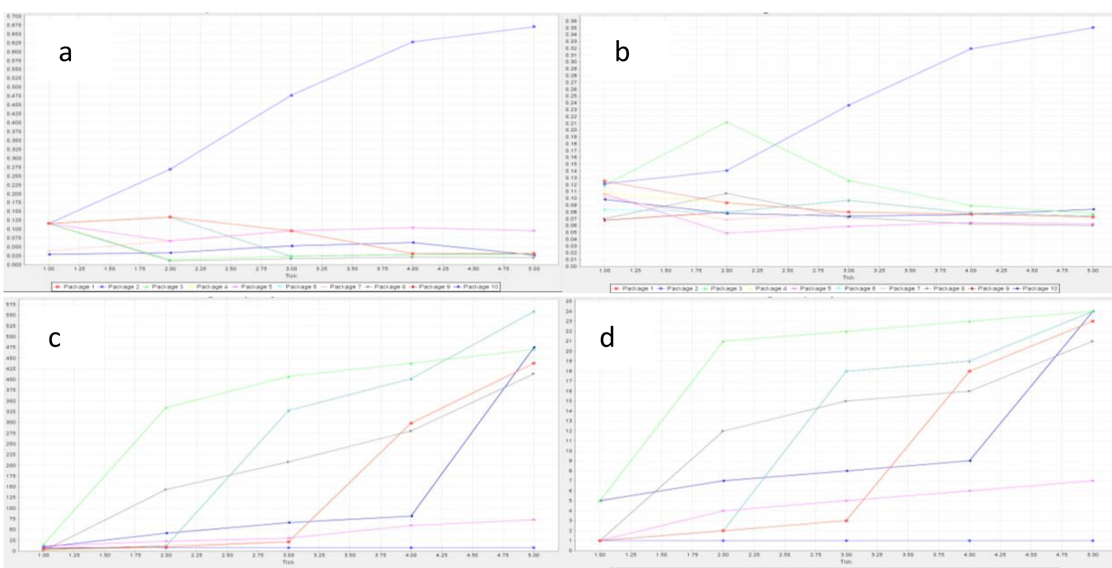

Figure 6 Example of assessment of the different policy packages based on the following criteria: (a) cost (100%) (b) performance based on cost (40%), time (20%) and effectiveness (40%) (c) institutional complexity (50%) and level of public unacceptability (50%) (d) level of risk (100%)

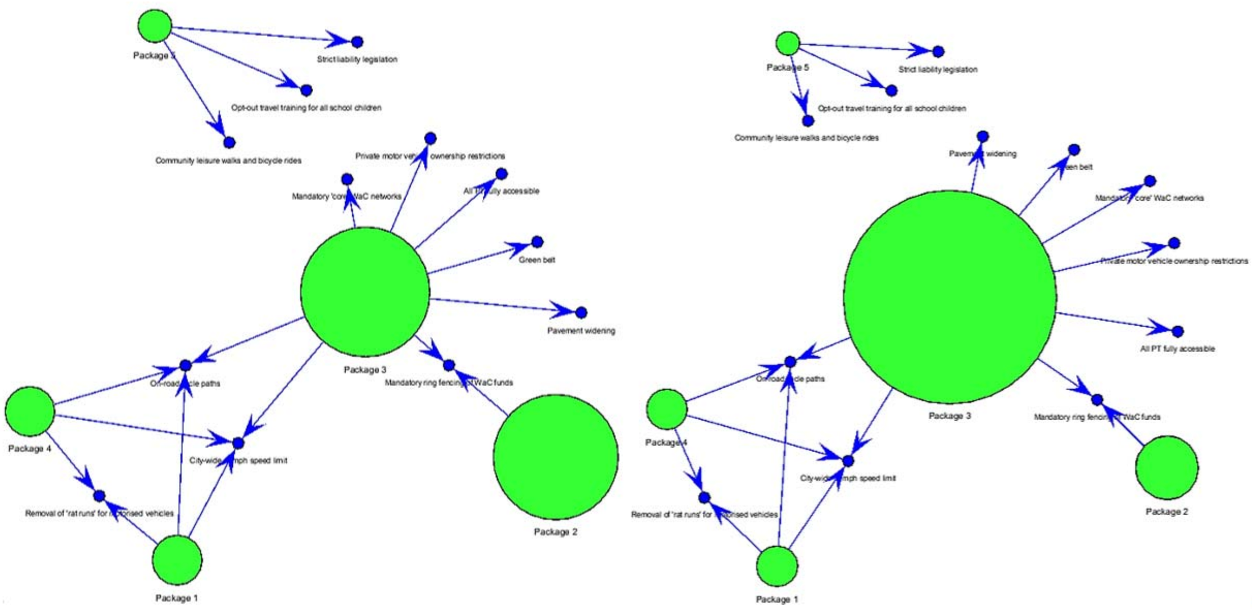

Figure 7 Policy packages scores based on (left) default criteria weights: Cost (40%), Time (20%), and Total effect (40%); and (right) modified weights: Cost (20%), Time (10%), Total effect (70%).

6. Conclusion and Future Work

Our efforts have focused on enhancing a previously developed decision support system for the formulation of policy packages with the aim of addressing some of the policy design challenges emerging from the complex nature of many policy problems. We have proposed to use an ABM system as a virtual environment for the exploration and analysis of different policy measure configurations in order to formulate and assess alternative policy packages.

Inspired by ideas that originate in engineering design and complexity science, we have highlighted the potential of an ABM system in facilitating the design of more effective, synergistic and reinforcing policies while avoiding internal contradiction within the policy packages. The approach combines techniques such as conceptual design, network analysis, ABM, multiple criteria decision analysis and negotiation and offers an interactive mode in which direct user input is used for critical decisions.

The ABM policy packaging system utilizes the information about the interaction of policy measures alongside user preferences and the attributes of the policy measures. The approach enhances the ability of the policy makers to systematically consider a large number of policy measures, configure and analyze different policy packages in a shorter period and at a greater depth. It provides real-time feedback and a variety of visualization options to help policy makers grasp the implications of their choices, and can highlight the possibility of reaching consensus among stakeholders with different criteria and priorities in cases where alternative policy packages have similar performance.

The results presented in this paper demonstrate the usefulness of adopting a systematic approach and of using a computational methodology to address generic complexities inherent in the formulation of policy packages. Although we have used the approach so far for transportation and environmental policy at national and metropolitan scale, the approach is relevant to other sectors such as energy, water, food or health and can have different geographical scopes.

The work presented in this paper has introduced a number of original ideas regarding the generation and analysis of policy packages. We plan to enhance and expand the system by adding the following features:

• Explicit consideration of geography and the integration with Geographical Information Systems: at present, the extent to which a policy measure is implemented is not considered although it will affect the implementation complexity and level of effectiveness of the measures.

• A more detailed consideration of temporal factors: considering the effects of a failure or a delay in the implementation of a policy measure, replacement of a policy measure with a new policy measure with different characteristics, or failure to take account the risks and uncertainties that could affect the policies is important.

• Exploring the use of ontologies: The use of ontologies [38] could be advantageous for the ABM system as it will provide the ability to represent concepts, their properties and relations, the use abstraction, and support reasoning. Transition from databases can be achieved by the development of ontologies for the specific domains under study (transport and environmental policy in this paper).

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