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Towards An Intelligent Agent-Based Multi-Criteria Group Decision Support System : A Case Study In Land Use Management

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Abstract: The Land use management constitutes a multi-dimensional issue affected by a variety of criteria of different significance. Many decision-makers (DMs) are involved in this type of dilemma, and their preferences are often in dispute. To address these issues, researchers created a variety of GDSS with various architectures; nevertheless, not all of them can apply artificial intelligence approaches to mimic human behavior by predciting or classifying solutions. In this work, the authors used a previously designed GDSS named WIM-GDSS as the foundation for developing a new one with various features; the two systems differ in the prediction model employed. The proposed system's prediction module employs a model trained on a multicriteria method known as PROMETHEE II rather than TOPSIS; the latter method is widely used in the literature and provides more choice and flexibility to the user when expressing preferences (more subjective parameters than TOPSIS). The paper includes a real case study in territorial planning, in which the proposed system would manage a group decision-making process for selecting the most suitable vacant zones for housing building. A coordination protocol will ensure DMs cooperation. The AHP approach will be used to assign criteria weights based on the preferences of DMs. This system includes a prediction module that predicts solutions rather than calculating them using a prediction model. In order to choose the optimal model, a comparison study was done between two models: Linear Regression (LR) and Multi Layer Perceptron (MLP). The results suggest that the MLP model is more suited to PROMETHEE II than the LR model, with a 95% accuracy. Future study will broaden the trials to include fuzzy logic approaches and completely integrate the proposed system with the geographic information system.

Keywords: Group Decision Support System, Multi agent system, Multiple Criteria Analysis, PROMETHEE II GDSS Method, Artificial Intelligence, Prediction Models, Machine Learning, Collaborative Decision

1. Introduction

Decision-making entails evaluating a variety of options (possibilities) in order to rank, choose, or classify them according to a set of criteria. Single-criteria cases are not suited for real-world requirements, which is why multicriteria decision support is used instead. It aims to handle this issue by allowing decision-makers to select and rank solutions based on their importance, while taking into account the influence of multiple criteria. Another aspect that needs to be treated is the number of decision-makers involved. In real -world organizational decision-making problems, decisions are often taken in meetings, where several members around the table are part of the final decision, which is why the non-efficiency of single-actor decision-making systems and the use of what is called group decision support systems (GDSS). Due to globalization, many companies are becoming multinational organizations, and their managers are traveling around the world to different (distant) places with different time zones, which makes them unavailable to participate in decisional meetings. To overcome this issue, many GDSSs are adapted to use a web-based architecture, which allows decisions to be taken properly regardless of the managers' whereabouts. Artificial intelligence has piqued the interest of scholars in recent decades because of its benefits in prediction, classification, and optimization. Nevertheless, few GDSSs in territory planning have explored these approaches. The current study consists of elaborating a GDSS based on a system called WIM-GDSS (Web Intelligent multicriteria Group Decision Support System) developed in [1]; like WIM-GDSS, the proposed system incorporates four tools, which are Multi-Agent System, Geographic Information System, multicriteria Analysis methods (TOPSIS and AHP), and artificial intelligence techniques (Multi-layer Perceptron and Linear Regression). The novelty of this new system is the prediction model used within. It is trained using

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the PROMETHEE II multicriteria method. The goal is for the prediction module to be capable of predicting PROMETHEE II results without having to use it, since the latter multicriteria method is widely used in the literature and provides the user with more subjective parameters concerning the problem's criteria. The model was chosen after conducting a comparison analysis between a linear regression model and a multi-layer perceptron neural network. The system's goal is to assist a group of decision-makers in reaching a compromise solution that satisfies the majority of them, or ideally all of them, while taking into account their preferences (often conflicting) and their remote locations. The scenario under consideration is a real-world case study in which the decision-makers concerned must work together to select the best vacant zone for the construction of a dwelling. The paper is structured as follows: Section 2 presents the related works, followed by our motivations and contributions in Section 3. In Section 4 the proposed model is describes alongside with its modules and components. Section 5 highlights a real case study in territory planning, with a comparison analysis conducted to select the appropriate prediction model with the best performance. Finally the paper is closed with a conclusion and future work in section 6.

2. Related Work

Since the consistency of decisions taken is one of the most critical factors determining an organization's performance, decision support has a significant effect on the business world. Several frameworks that treat various forms of decision-making problems have been established in the decision support domain over the years; however, this domain can be divided into two broad categories:

- Single-actor decision issues involve only one decision-maker who formulates an option (solution) based on his personal beliefs and opinions (preferences).
- Multi-actor decision issues entail multiple deciders (decision-makers) coming to an agreement (compromise solution), each with his or her own set of personal interests that are often at odds with those of others.

Several decision support frameworks in TP (Territory Planning) have captured our attention in the context of single-actor decision support. Some of them are briefly summarized below:
multicriteria analysis In [2], was employed as a tool to determine the positioning of high human pressure areas in space. In the same work, a case study of the Algerian department of Naama was presented. Several spatial tool-rich decision-making support systems and multicriteria methodologies for managing and deciding on territorial problems were developed (water, air, natural areas, transportation, energy, waste, health planning, risk management etc) [3]. All these systems integrate multicriteria tools in the analysis of GIS (Geographic Information System) at various levels, but they consider the criteria to be independent and not able to model interactions (interchangeability, correlation, preferential dependence etc), the authors In [4], have already addressed the importance of using correlation criteria in MCDA methods, specifically "ELECTRE TRI," by using the Choquet integral (rather than the arithmetic sum) as an aggregation operator. Traditional decisional models tailored to the case of a single decision-maker, on the other hand, are incompatible with organizational reality.
Collective decision support, also known as Group Decision Support or Multi-participant Decision, refers to processes involving multiple decision-makers.
According to [5] decision processes in organizations often include many actors interacting with one another, for [6]a GDSS should facilitate and record group communication processes and should take into account the likelihood of communication occurring outside of the system; therefore, traditional decision models that are based on a single decision-maker are often not suited for such situations. Some of the systems built in the sense of multi-actor decision support are listed below:
The authors in [7] proposed SmartScapeTM, a web-based spatial decision support system (SDSS) that aims to assist decision-makers in evaluating and assessing cultural changes in agricultural landscapes on a variety of ecosystem services, in [8] the authors presented and implemented an information decision support system (IDSS) aimed at assisting decision makers (construction engineers) in the efficient execution of a new transmission line project, [9] proposed an interactive dynamic web-based architecture for an urban climate adaptation tool called UrbanCAT, whose main goal is to assist cities in planning potential threats related to urban infrastructure and population due to climate change.
[10] presents a novel Decision Support System (DSS) to rank-order management options (i.e. scenarios) in the water resources management system of Tehran metropolitan region, Iran. The DSS is based on Social Choice Theory (SCT). In [6] the authors proposed a decision support framework for the management of space processes, a multi-criteria approach, and a negotiation approach, in which two components were combined in this model: a multi-agent system dotted with a negotiation protocol to ensure group decision process, and a geographical information system to handle spatial data, [11] proposed a group decision support system modeled by a multi-agents system. The author used a negotiation protocol based on argumentation approach, which enables agents (decision-makers) to share complex justification positions rather than only simple proposals. The systems listed above are not dotted with intelligence mechanisms; instead, the authors used reactive agents to represent decision-makers in most cases, with the exception of [11] where the authors used BDI (beliefs, preferences, intentions) agent architecture. There haven't been many intelligent systems built in the sense of territory planning using MAS (Multi Agent System) and GIS combined with multicriteria analysis, to our knowledge, the authors in [12]

suggested a model for shopping center site selection using a hybrid fuzzy multicriteria decision making (fuzzy AHP and fuzzy TOPSIS) method. In [13] the authors presents a decision support system (DSS) modeled by a fuzzy expert system (FES) for medical diagnosis to help physicians make better decisions. In [14] proposed an intelligent decision support framework for classifying industrial sites using a geographic information system, expert knowledge, and machine learning techniques to approximate quality requirements. For generating position alternatives, the proposed system uses a geographic information system and a hierarchical neuro-fuzzy approach for site classification. The neuro-fuzzy approach is built on a knowledge base created by industry experts. The authors in [15] proposed A temporal distributed group decision support system based on multicriteria analysis for solving spatial localization in territory planning problems. The authors used a multi-agent system to model the agents and a negotiation protocol to reach an optimal consensus solution before set deadlines using decision trees in the process.
The work in [16] proposed a data mining based decision support system employing a hybrid approach combining decision tree and artificial neural network to predict the marketing strategies for an organization. The authors In [17] developed a novel framework for detecting and monitoring heart failure infected individuals based on computer assisted diagnosis and IoT. With unclear information, the suggested healthcare system tries to improve diagnosis precision. The authors propose a neurosophic multi criteria decision making (NMCDM) approach to help patients and doctors determine if they have heart failure. [18] proposes an integrated approach towards rapid decision-making in the agricultural sector aimed at improvement of its resilience. First, they introduced a multi decision-making framework for group decision-making based on the Pugh matrix technique. The impact of perturbations in the criterion weights are tested using a Monte Carlo simulation. Then they separate the elements that contribute to agricultural resilience into three categories (food security, agricultural viability, decent jobs).

3. Contribution

Finding a consensus decision (solution) among multiple decision-makers (actors) while taking into account each one's different point of view is what group decision making support entails. In order to achieve a suitable solution for all parties involved, authors typically used a mixture of strategies such as negotiation [19], voting [20], argumentation based systems [11], monotonous concession [20], WIM-GDSS [1] entails a three-phase coordination protocol based on the PROMETHEE II GDSS method illustrated in Figure 4 proposed in[21]. The multicriteria method used in WIM-GDSS is TOPSIS, which is known for its straightforwardness and simplicity, and the prediction model used is linear regression (which has proven its efficacy in WIM-GDSS), however, TOPSIS has only one subjective parameter (criteria weights), whereas PROMETHEE II has several, giving the decision-maker more freedom and flexibility when expressing his preferences. By changing the multicriteria used, a new model selection procedure has to be conducted in order to choose the most suited model (since linear regression extract only linear patterns and could not perform very well with PROMETHEE II method). The authors in this work improved WIM-GDSS by changing the methods and models used within. The major contributions are listed below:

- Using the PROMETHEE II method instead of TOPSIS method as basis for the multicriteria module within the system.
- Train a prediction model on PROMETHEE II ranking vector, by doing so the new model will have the ability to predict a ranking solution for similar problems without using PROMETHEE II which benefits in time complexity.

4. The Proposed System

In this paper, the authors used the same web-architecture adopted by WIM-GDSS (Figure 1), in which two levels constitue the system:

- The client side has two modules which are namely: the web user interface, the geographic information system (GIS)
- The server side includes the multi-agent system and the database system modules.

There are three physical modalities for integrating GIS to decision support systems: loose, tight, and full integration. The authors chose the loose coupling which consist of running the two systems independently with the ability of sharing files, this choice was due to its simplicity and low cost development.

1) Web user interface: a web user interface or web app allows the user to interact with content or software running on a remote server through a web browser. The content or web page is downloaded from the web server and the user can interact with this content in a web browser, which acts as a client.
2) GIS: according to the authors [22] 80% of the data used by decision makers for industrial site selection (which is a territory planning problem) is geographical (spatial). Therefore the importance of GISs for this kind of problems.
   GISs are mainly used to: [23] Capture, store, query, analyze, display output spatial information.
3) Web server: a web server is a set of computers (or one) that constitute a system running software satisfying client requests (HTTP), in our case the user (decision maker) will get the appropriate spatial information from the GIS to request the web server which contains the MAS module responsible for the execution process and then return the appropriate response to the decision-maker (web user interface).

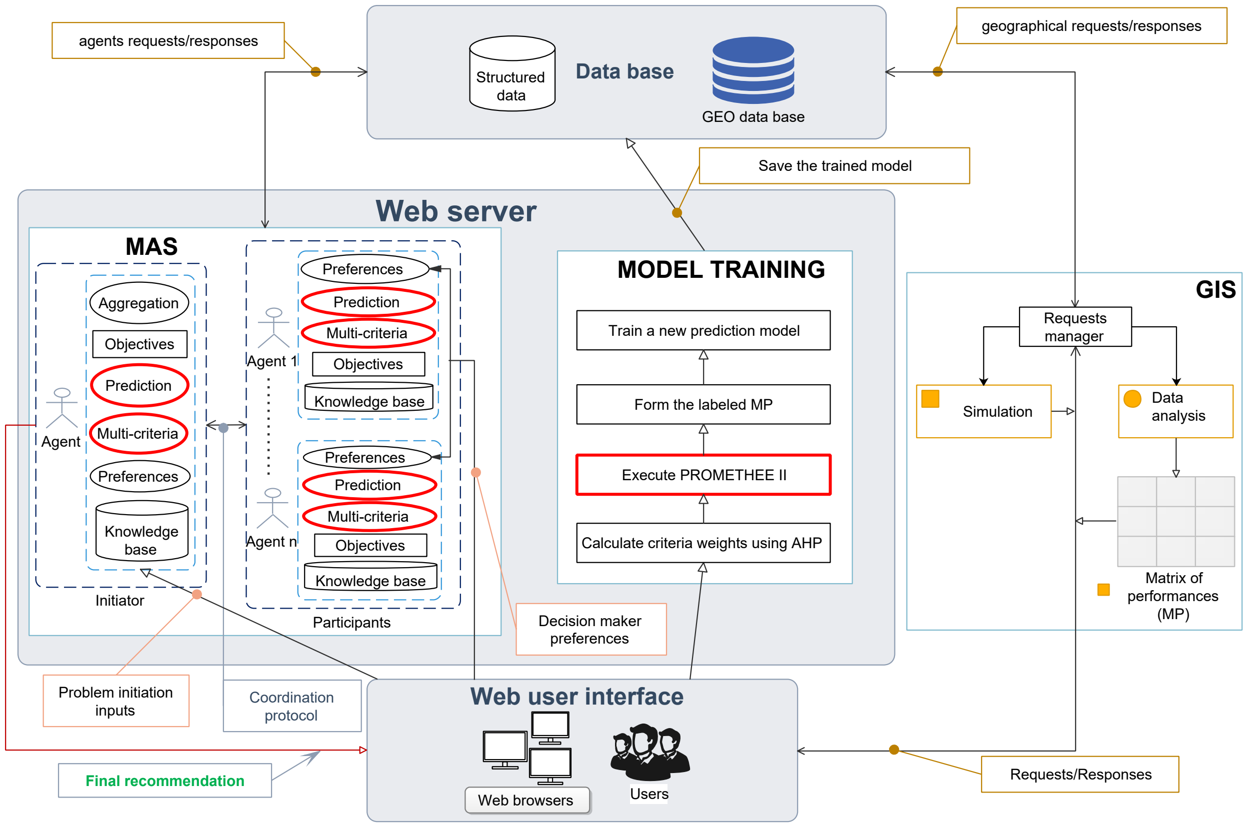


Figure 1. Global architecture

4) MAS: it is used to represent and deal with the multiplicity and diversity of decision-makers involved in the decisional process, this representation will preserve the autonomy and valuable intelligence and knowledge provided in face to face meetings, in literature, there are a lot of tools to implement such a system depending on what is needed and in which development language, in, our case we used a python based multi-agent system called SPADE (smart python agent development environment) [24] to fully exploit the python language power when it comes to implementing artificial intelligence methods.
5) Web Database: is an application designed to be accessed and managed through the internet, it contains a collection of data (often structured). The operators in the web server can manage this data and use it to satisfy client requests.

Figure 1 illustrates the proposed system's architecture; the components highlighted in red correspond to modules (multicriteria and prediction modules) that have been changed since the system presented in [1].

A. *The Multi agent system module*

The multi-agent concept is a strong tool that allows a group of decision-makers to engage in the decision-making process using a coordination protocol to arrive at a consensus solution; it successfully compensates for GIS inadequacies.

In this paper, the model used for the agents is based on the work proposed by Javier Palanca in [24] which is a python-based framework called SPADE, the novelty in this current study is that the latter agents will be dotted with additional modules (see Figure 2) that allows it to use multicriteria methods and machine learning techniques to resolve the given problem.

As shown in Figure 2, several modules compose the agent namely: Connection module, Message dispatcher, Behaviors, Knowledge base, Prediction module, multicriteria module, Aggregation module.

1) *The agent's model of SPADE platform*

The Agent Model in the spade platform [25] is made up of a platform connection mechanism, a message dispatcher, and a set of different behaviors to which the dispatcher sends messages.

To connect to the XMPP server, each agent requires a

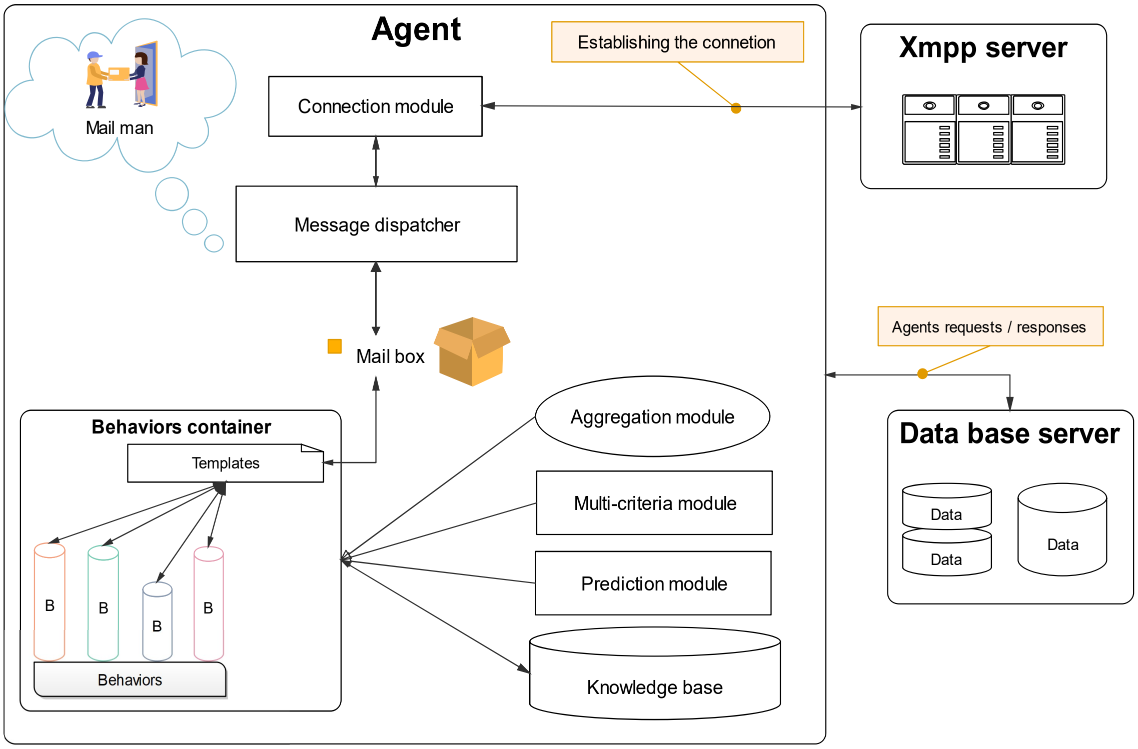


Figure 2. Agent architecture. (source: [1])

Jabber ID, also known as a JID, and a valid password. The JID (which consists of a username, a @, and a server domain) will be the name used to identify a platform agent, such as myagent@myprovider.com.

1) Connection to the platform:
The XMPP protocol is used internally in SPADE to handle communications. This protocol includes a mechanism for registering and authenticating users with an XMPP server.
Following a successful registration, each agent maintains an open and persistent XMPP communication stream with the platform. This process is initiated automatically as part of the agent registration process.
2) The message dispatcher:
Internally, each SPADE agent has a message dispatcher component. When a message for the agent arrives, the message dispatcher puts it in the appropriate ”mailbox,” and when the agent wants to send a message, the message dispatcher takes care of it, placing it in the communication stream. When a new message arrives or is about to be sent, the SPADE agent library dispatches it automatically.
3) The behaviors:
An agent can perform multiple actions at the same time. A behavior is a task that an agent can carry out by following a set of instructions. SPADE comes with several predefined behavior types, including cyclic, one-shot, periodic, time-out, and finite state machine. These behavior types aid in the implementation of the various tasks that an agent can perform. A SPADE agent can support the following types of behaviors:
   - Cyclic and Periodic behaviors are useful for performing repetitive tasks.
   - One-Shot and Time-Out behaviors can be used to perform casual tasks.
   - The Finite State Machine allows more complex behaviors to be built.

   Each agent can have as many behaviors as they want. When a message arrives at the agent, it is routed to the appropriate behavior queue by the message dispatcher. A message template is associated with a behavior. As a result, by matching the message with the appropriate template, the message dispatcher determines which behavior the message is for. Using templates, a behavior can thus select the type of messages it wants to receive.

In addition to the spade default components, we added another three modules, the multicriteria module, the prediction module and the Aggregation module.

B. The multicriteria module

This module is in charge of dealing with conflict among criteria by employing multicriteria analysis methods. Given the nature of the problem, any type of multiple-criteria analysis family could be used, however the authors chose the outranking family methods, which assist the decision maker by providing an ordered vector of alternatives associated with a preference degree indicating how much one alternative is better than the next, the resulting vector does not eliminate any of the options. PROMETHEE II [26], [27] and its extension PROMETHEE II GDSS [21] are the multicriteria methods utilized in this article. The PROMETHEE II approach is utilized locally by each agent to build its own ranking vector of alternatives (objective vector), whilst the PRMETHEE II GDSS method is used globally to find the collective solution (taking all participants' objective vectors into consideration).

1) The PROMETHEE II method

The Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) belongs to the outranking family of MCDA methods.
PROMETHEE results to a ranking of actions (as the alternatives are known in the method's terminology), and is based on preference degrees.
PROMETHEE II has been applied successfully in various applications domains [28] (Table I)

TABLE I. Distribution of papers on PROMETHEE by application areas

Domain	N°	%
Environment management	323	21
Public services and applications	277	18
Industrial applications	243	15.8
Energy management	130	8.5
Water supply management	98	6.4
Finance	96	6.3
Transport	59	3.8
Supply chain	51	3.3
Other domains	68	4.4

According to Brans and Mareschal [27] this method is suitable for problems of the kind:

$$\max\{g_1(a), g_2(a), ..., g_n(a) | a \in A\} \tag{1}$$

Where:

- A is a finite set of feasible alternatives (actions)
- J is a finite set of criteria having j varying from 1 to n
- $g_j(.)$ are the evaluations of A against J

The decision maker needs to construct the evaluation table (see Figure II) taking into account that the evaluations should be real numbers. The second row in the evaluation table w_j represent the weights associated to the criteria to reflect their importance against each other, Equation.(2) holds true:

$$\sum_{j=1}^{n} w_j = 1, j = 1, 2, ..., n \tag{2}$$

TABLE II. Evaluation table (Decision matrix)

a	$g_1(\cdot)$	$g_1(\cdot)$	$\cdots$	$g_n(\cdot)$
	w_1	w_2	$\cdots$	w_n
a_1	$g_1(a_1)$	$g_2(a_1)$	$\cdots$	$g_n(a_1)$
a_2	$g_1(a_2)$	$g_2(a_2)$	$\cdots$	$g_n(a_2)$
$\cdots$	$\cdots$	$\cdots$	$\ddots$	$\cdots$
a_m	$g_1(a_m)$	$g_2(a_m)$	$\cdots$	$g_n(a_m)$

Preference degree is value between 0 and 1, that represent the deviation between the alternatives regarding each criterion, in order to calculate these degrees, a preferably function (generalized criterion) should be specified for each criterion, taking into account the criterion's optimization (maximized /minimized), and a set of subjective parameters (see table IV), the authors of the method propose six different types of preferably functions, as shown in Table III; these types have been accepted and used widely in the literature [29].

the preferably function describes the attitude of the decision maker towards the difference between alternatives for a given criterion. PROMETHEE results to a ranking of actions (as the alternatives are known in the method's terminology) and is based on preference degrees. Steps include:

- **The pairwise comparison of actions on each criterion:** in this level, the preferably weighted index π is calculated as defined in 3, this index indicate the preferably percentile between each pair of the alternatives over all of the criteria.

$$\pi(a, b) = \frac{\sum_{j=1}^{n} P_j(a, b) w_j}{\sum_{j=1}^{n} w_j} \tag{3}$$

- **The computation of uni-criterion flows:** n every alternative two flows should be calculated (see 4, 5)
  - the leaving flow (ϕ^+) which indicates how much the alternative is preferred over all the others.

TABLE III. Preference functions

Figures/Usual.jpg	Type 1: Usual	This is the most basic preference function of them all. It includes no thresholds and returns a binary value : • Two identical actions (difference = 0) are indifferent (degree of preference = 0). • Two actions with different values (difference ¿ 0) generate complete preference (degree of preference = 1) even if the difference is negligible. This type of preference function should be used with great caution, as it is incapable of distinguishing between very small differences (which may be negligible) and much larger differences.
Figures/U shape.jpg	Type 2: U-Shape	The U-Shape preference function introduces the notion of indifference threshold (Q) but remains binary : • Two actions with high similarity (difference *leqQ*) are indistinguishable (degree of preference = 0). • Two actions with highly divergent values (difference > *Q*) generate a complete preference (degree of preference = 1) In practice, its utility is quite limited.
Figures/V shape.jpg	Type 3: V-Shape	The V-Shape preference function introduces the notions of preference threshold (P) and variable degree of preference : • Two identical actions (difference = 0) are indifferent (degree of preference = 0). • Two distinct actions (difference *succP*) generate a preference with a complete degree of preference (degree of preference = 1). • Two actions with smaller relative differences (difference *leqP*) generate a degree of preference proportional to the difference (degree of preference = difference / P).
Figures/Level.jpg	Type 4: Level	The Preference function of type ”Level” has two thresholds: Q and P. Three distinct cases emerge depending on how these thresholds are defined : • Two actions with high similarity (difference *leqQ*) are indistinguishable (degree of preference = 0). • Two highly distinct actions (difference *succP*) generate a preference with a complete degree of preference (degree of preference = 1). • Between the two, two actions with varying degrees of preference (*Qprec*difference *leqP*) generate a low degree of preference (degree of preference = 1/2).
Figures/Linear.jpg	Type 5: Linear	Likewise, two thresholds are included in the linear preference function : Q and P. The primary distinction between the type 4 (Level) preference function and the Linear preference function, is that the degree of preference increases linearly between the Q and P thresholds: • Two actions with high similarity (difference *leqQ*) are indistinguishable (degree of preference = 0). • Two highly distinct actions (difference *succP*) generate a preference with a complete degree of preference (degree of preference = 1). • Between the two, two actions with varying values (*Qprec*difference *precP*) generate a degree of preference that increases linearly from 0 to 1 as the difference between Q and P increases (degree of preference = (difference - Q) / (P - Q)).
Figures/Gaussian.jpg	Type 6: Gaussian	Gaussian preference functions were developed as a substitute for linear preference functions (type 5). It is more spherical in shape, with no flat indifference and complete preference zones. At the same time, it is devoid of indifference or preference thresholds. Its shape is determined by another parameter: the Gaussian threshold S, which indicates the position of the preference function's point of inflection. In practice, the threshold S must lie between the thresholds Q and P, as it corresponds to a degree of preference of 0.39. However, it is more difficult to define than the Q and P thresholds.

- the entering flow (ϕ^-) which refers to how much all the other alternatives are preferred to this alternative.

$$\phi^+(a) = \frac{1}{m-1} \sum_{x \in A} \pi(a, x) \tag{4}$$

$$\phi^-(a) = \frac{1}{m-1} \sum_{x \in A} \pi(x, a) \tag{5}$$

- **The aggregation of the latter into global flows:** this step consist on aggregating the leaving and entering flows into the global flow as defined in 6

$$\phi(a) = \phi^+(a) - \phi^-(a) \tag{6}$$

At the end, the method's output is the set of alternatives associated with a global flows. The higher the global flow, the better the alternative.

TABLE IV. Subjective parameters

Parameter	Description
weight	measures of the importance of each used criterion
Preference threshold (p)	the threshold of absolute preference, above which there is a total preference to one of the two actions and assigning the preference degree the value of 1 [29]
Indifference threshold (q)	the threshold of indifference, below which there is no preference to either of the actions meaning the preference degree is 0 [29]
the inflection point (s)	which is an intermediate value between q and p, in case of a Gaussion function [29]

1) Why PROMETHEE II The PROMETHEE II method is among the most used methods in the category of outranking methods, because it offers a number of advantages of which we quote [30]:
   a) It integrates the recent developments in the modeling of preferences in a simple way.
   b) It has a mathematical basis, so that it programs and improves its functionality easily.
   c) It builds a valued outranking upgrade that reflects the preference intensity.
   d) It provides the decision-maker with a complete and partial ranking of the alternatives to choose.

   We chose the PROMETHEE II method because it deals with a large number of alternatives, whereas the other methods such as AHP or ELECTRE III treat a limited set of alternatives [31].
2) Why PROMETHEE II GDSS: the PROMETHEE II GDSS is an extension of PROMETHEE II method, the main reasons for using it are :
   a) Its capacity of Dealing with decision makers multiplicity and diversity.
   b) No need to use any negotiation or voting protocols to solve group decisions problems.
   c) It Exploits the PROMETHEE II method advantages by using it to solve the global problem formed by aggregating the decision makers objectives.
3) Why AHP: In any given multicriteria decisional problem, criteria have a great impact on the final results due to decision-makers preferences (they prefer some criteria over the others) therefore the need of assigning weights to the criteria to reflect their importance in the given decisional problem,

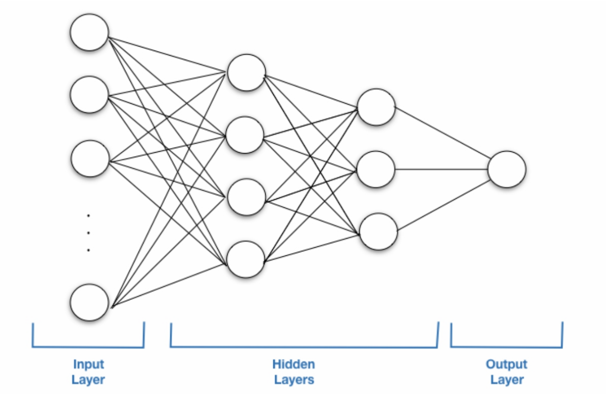


Figure 3. Multi-layer perceptron architecture

AHP method is a widely used MCDA methodology proposed by Saaty [32], "It has been one of the most widely used multiple criteria decision-making tools" [33], "It is used by decision makers and researchers, because it is a simple and powerful tool" [34].

C. The prediction module

The Artificial intelligence techniques and methods can be classified according to the final objective (classification or prediction) and the amount of supervision during the training phase (supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning). In this study, the authors aim to predict a scoring value of each one of the alternatives in the dataset. The final objective is to get an ascending ranking (from the best to the worst) depending on the predicted scores. For this end, a supervised learning algorithm for prediction is used. The dataset will be associated with a score to give full supervision during the training phase. These scores are calculated using the multicriteria method PROMETHEE II. After preparing the dataset, the latter will be feed to a neural network designed to give the desired predictions.

- The neural network architecture: the multi-layer perceptron MLP architecture is one of the most popular and basic architectures for prediction and regression analysis in the realm of neural networks. As shown in Figure 3, the MLP regressor used consists of three layers and employs a feed-forward Back-error Propagation (BP) learning method.
  - Input layer: having n neurons (n: number of features)
  - Hidden layers: having m neurons
  - Output layer: having 1 neuron (the neuron having the score value)

D. The aggregation module

This module is dedicated to the initiator role, its main objective is to concatenate the decision-makers involved

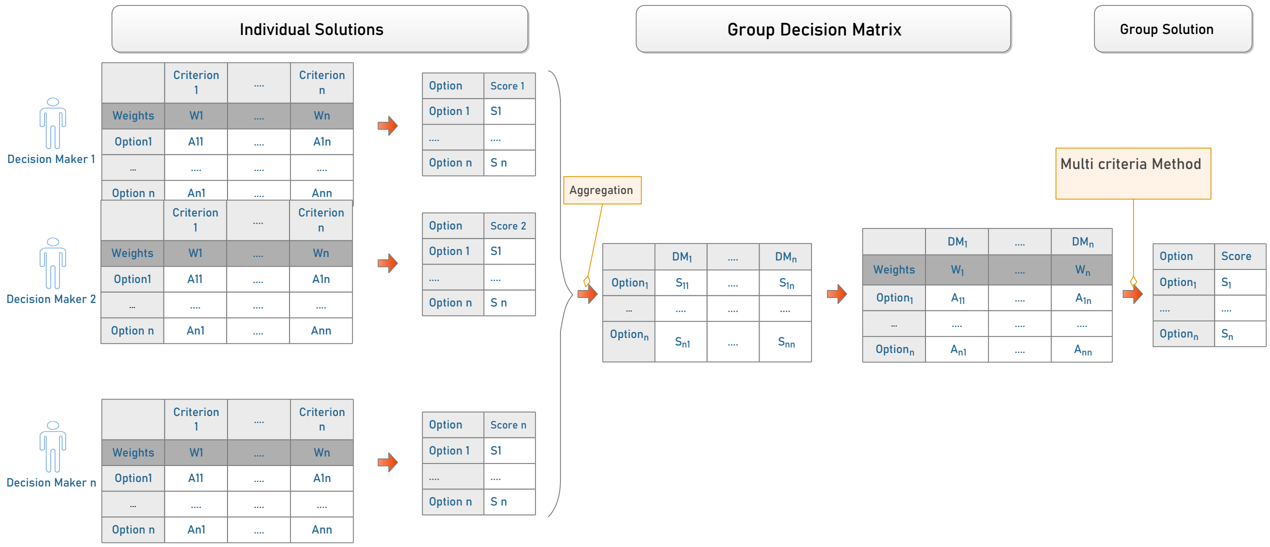


Figure 4. PROMETHEE II GDSS procedure

objectives vectors (see phase 3 in Figure 4), to form a global matrix of performances. The latter matrix contains alternatives evaluations over each decision-maker.

E. Decision making process adopted by WIM-GDSS

As mentioned before in WIM-GDSS, a multi-agent system is integrated into the webserver level. The main objective is to use its virtual agents to model real decision-makers within the system.
Two major roles could be identified: Administrator and decision-maker, in this section we are interested in the decision-maker role.
When login to the platform a corresponding agent will start having two possible sub-roles to play on the decisional process, these sub-roles are attributed as follows:

- The agent is an Initiator if its decision-maker is the one who initiated the problem.
- The agent is a participant if its decision-maker has been invited to participate in the decisional problem.

The agent in WIM-GDSS is dotted with two Finite State Machine behaviors, one for each role.

1) Pseudo algorithms

In the pseudo algorithms 1 and 2, we will see the difference and interaction of these roles in the decisional process when a new problem is initiated. For acronyms definitions refer to Table V.

Algorithm 1: Initiator role

```
Input: MP, LD, WD, AT, Deadline, subjective
       parameters(P,Q,S), CP
Output: Final ranked alternatives vector;
1  initiate the problem (initiator inputs);
2  CW = AHP(CW): use AHP to calculate criteria
     weights;
3  Invite(LD): send invitation to decision makers;
4  if Deadline OR All responses received then
5      nbA = count number of acceptances;
6      if nbA ≥ AT then
7          if model exist then
8              predict ranking vector:MODEL(MP,CW);
9          else
10             PROMETHEE II (MP,subjective
                 parameters,CW);
11             Build a labeled MP using PROMETHEE II
                 results;
12             Train a new model;
13             Save the new model;
14         end
15         Inform(): send execution message to decision
             makers;
16         Aggregate the ranking vectors to form GMP;
17         Repeat Step7 to Step13 using GMP
18     else
19         Abort(): send abort message to the decision
             makers;
20     end
21 end
```

Algorithm 2: Participant role

```
Input: Response, subjective parameters(P,Q,S), CP
Output: Local ranking of alternaves vector
Responde(): send response (accept or refuse) to
  initiator;
if execute order received then
    CW = AHP(CW): use AHP to calculate criteria
      weights;
    if model exist then
        predict ranking vector :MODEL(MP,CW);
    else
        PROMETHEE II (MP,subjective
          parameters,CW);
        Build a labeled MP using PROMETHEE II
          results;
        Train a new model;
        Save the new model;
    end
    Send(): send the ranking vector to the initiator;
else
    Abort(): send abort message to the decision
      makers;
end
```

F. The coordination protocol

A protocol is required in any group decision support system to ensure the cooperation of the actors involved in the process in order to find a satisfying solution for the majority of them; several protocols have been utilized in the literature such as negotiation, voting, reasoning, and so on (section 3). The authors employed a coordination protocol in the current study to animate the cooperation between the participants (decision-makers) in WIM-GDSS, the latter protocol employs the PROMETHEE II GDSS procedure (Figure 4) established in [21] to deal with collective decision-making. As in [1] the protocol is tailored to the system's requirements. Figure 5 provides an overview of the later protocol, and Figure 6 depicts the three phases that comprise it. The following are the phases:

- **Phase One**: Generation of alternatives and criteria by the decision-maker who initiates the decisional problem (initiator) and then invites the decision-makers involved, check for problem validity by comparing the number of accepted invitations against the acceptance threshold.

- **Phase Two**: Individual evaluation by each decision maker after receiving the execute order from the initiator. In this phase each participants introduce his preferences (p, q, v), after forming a pairwise comparison matrix of criteria evaluations, the AHP method is used in this level to calculate criteria weights for the corresponding decision maker, the latter's agent check for model existence in accordance with the preferences introduced, and use it to predict the ranked vector of alternatives. If the model does not exist then the PROMETHEE II method is used to calculate the objective vector. In this level the PROMETHEE II method wil be used to train a prediction model using the introduced preferences and problem's dimensions (number of criteria and number of alternatives) and save the obtained model for further use.

- **Phase Three**: Global evaluation by the group is where the initiator aggregates all the decision makers' objectives (rankings) and forms a global matrix of performances (GMP), the AHP method is used to attribute weights to decision makers (equally important), then the same procedure after searching for model's existence from **Phase Two** is conducted having as input the weighted GMP. The final objective vector obtained represent the collective solution of the group decision-making problem.

The acronyms in the sequence diagram depicted in Figure 6 are described in Table V.

G. Communication

The XMPP protocol is utilized in SPADE to manage all internal interactions; this protocol allows agents to send and receive messages from one another (message to message). The chronology of these communications in the coordination protocol is depicted in Figure 6. The messages exchanged are defined in Table VI.

TABLE V. Acronyms

Acronym	Description
MP	A collection of data describing the decisional problem; it is a two-dimensional matrice with columns for criteria and rows for alternatives, and the material for the evaluations of alternatives against the criteria.
LD	List of decision makers involved in the problem solving.
WD	Weights of the decision-makers: A list of decision-makers importance in the decisional problem.
AT	Acceptance Threshold: the minimum number of decision makers to launch the problem's resolution.
SP	Subjective parameters: Decision-maker preferences (weight, preference and indifference of the criteria).
Initiate-problem	Initiate the problem by the initiator decision-maker, he introduces all the necessary parameters to describe the decisional problem.
Count-agree	Count the number of responses: Count the number of decision-makers who agree to participate in the decisional problem.
Verify-model	Verify if the model exists: Check the database if a model with the given preferences already exist.
PROMETHEE II	Preference Ranking Organization METHod for Enrichment Evaluations: Use PROMETHEE II method to rank the alternatives of the decisional problem.
Train-new-model	Train a new prediction model: Use the PROMETHEE II results to train a new prediction model to use in the future.
Save-model	Save the trained model in the database for further use.
Aggregate	Aggregate the decision-makers vectors of preferences: to form a 2d matrice using the decision-makers ranking solutions where the columns are the decision-makers NetFlows and the rows are the alternatives therefore the matrice will contain the NetFlow score of each alternative against each decision-maker.
Prepare-preferences	Preparing the decision-maker parameters: Setting the subjective parameters for the global matrix of performances.
AHP	It's a multi criteria method proposed by [32]. The acronym Stands for: Analytic Hierarchy Process. It is a method of "measurement through pairwise comparisons and relies on the judgments of experts to derive priority scales" [35]
GMP	Group Matrix of Performances: refer to the matrix of performances formed using decision makers' objective vectors.
CP	Criteria Preferences: a two dimensional matrix containing the evaluations of pairwise comparison of each criterion against the others.
WC	Weight of Criteria: the resulting vector of AHP method, representing the weights of the criteria.

TABLE VI. Primitives

Message	Description
Invite()	Invite the decision-makers to engage in the decision-making process.
Answer()	Send a response (accept or decline) to the initiator's request (whether to participate or not).
Inform()	Send an order to the decision-makers involved to begin their resolution (execute the decisional problem).
Abort()	Send an order to the decision-makers to halt the execution of the decisional problem.
Send-local-output()	Send the initiator the execution results (objectives).

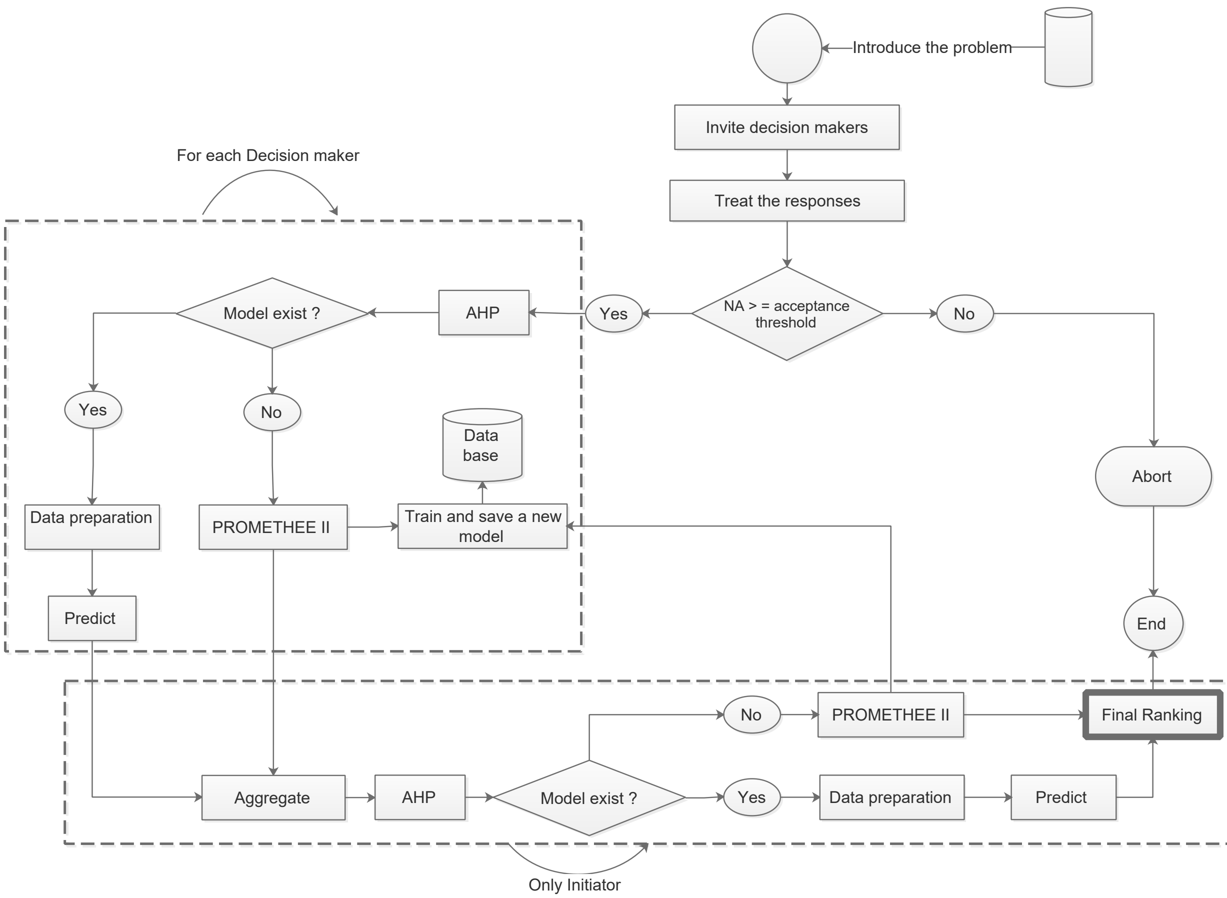


Figure 5. Flowchart of the coordination protocol

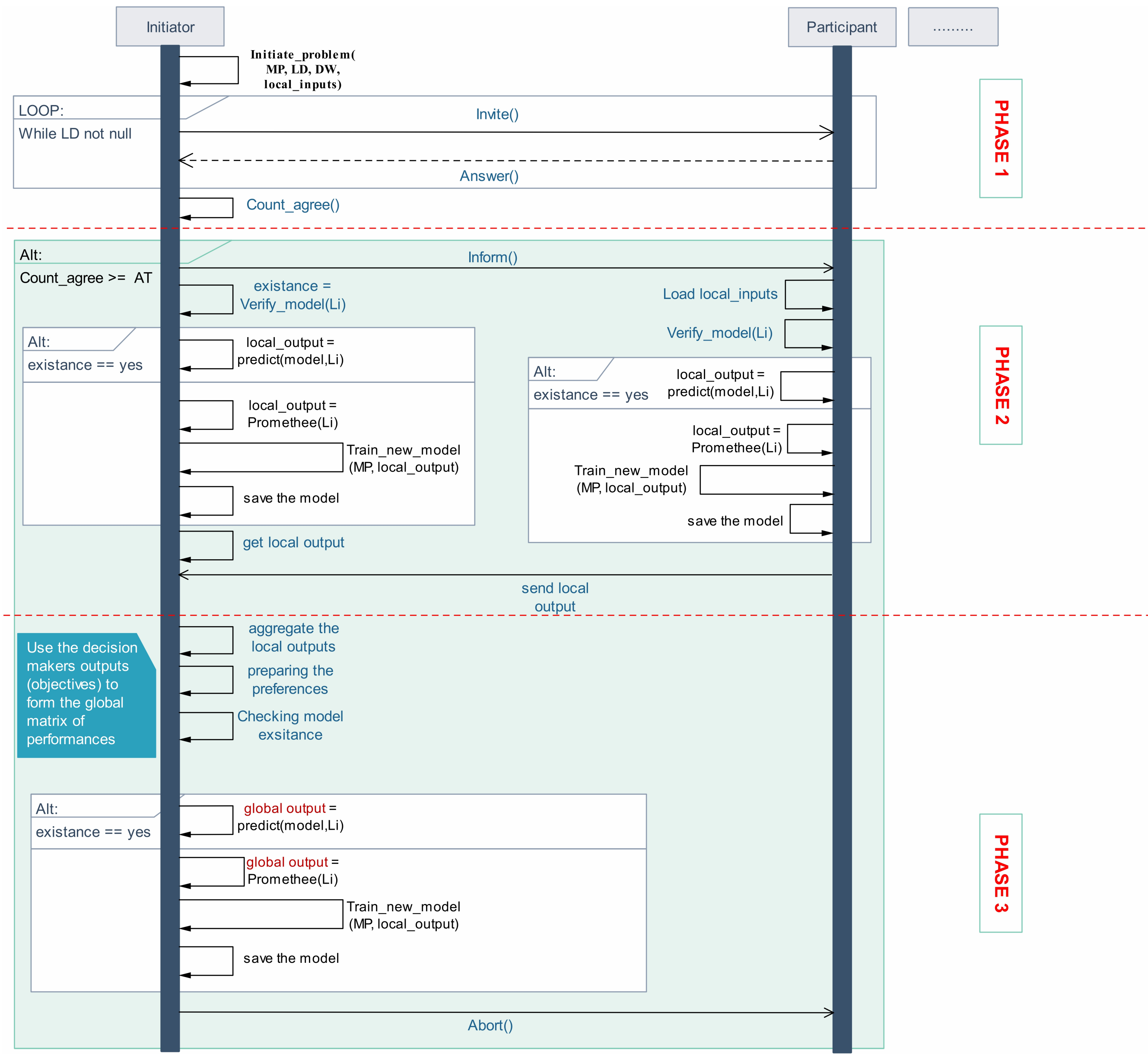


Figure 6. Sequence diagram for coordination protocol

5. Case Study

WIM-GDSS is based on web architecture, to implement such a system, we have to use different adequate tools in every level of the architecture:
We used a python web free open source framework called DJANGO [36] based on an MVT (model view template) architecture to handle our WIM-GDSS.
At the client level many web browsers (Mozilla, chrome, opera, safari, explorer...) could be used as a web user interface allowing the user to interact with the server level of the platform, for designing and displaying information, we used the bootstrap frontend framework and JQuery libraries.
The server-level is responsible for handling users' requests and responses (including interaction with the database level by requesting and retrieving information).
As mentioned above, WIM-GDSS need a multi-agent system at this level, developing such a tool is a very complex task, therefore we chose to use an existing platform called SPADE (Smart Python Agents Development Environment) [24], which is a free and open-source multi-agent platform based on python, this choice was based on:

- The simplicity of coupling the platform with the DJANGO framework (both using python).
- To exploit the power of python language when it comes to implementing artificial intelligence methods.
- It is a free and open-source framework.

At the database level, we used a MYSQL server to handle our database.
The suggested approach in this article seeks to rank a set of alternatives (actions) from best to worst in terms of meeting decision makers' needs for numerous criteria. The alternative ordering is connected with a score indicating the degree of preference (how one action is preferred against another action).

A. *The addressed problem*

In this article, we used an existing region as a basis of our study (with real data), the objective is to rank a set of empty zones to help decision-makers choosing the best adequate zone for the construction of a dwelling.
In this case study, we adopted the case brought up by Joerin in [37] and treated also by Hamdadou and Bouamrane in [19]. The study area is located in the Canton de Vaud 15 km from Lausanne in Switzerland, its area is about 52 000 km2, its geographical limits in the Swiss coordinating system are 532 750-532 500 (m) and158 000-164 000 (m). In this study, 650 empty lots (alternatives) were proposed, in addition to that, seven criteria were identified given the diversity of factors (environmental, social, economic, ...): Harm, Noise, Impacts, Geo-technical, Equipment, Accessibility, and Climate. The matrix of performance, depicted in Figure 7, is generated by the definition and assessment of the identified criteria according to different actions. The GIS component is in charge of this matrix.

N°	ID_ZONE	HARM	NOISE	IMPACTS	GEOTECH	EQUIP	ACCESS	CLIMATE
1	202	1,00	0,68	0	1	816	8	0,92
2	209	1,00	0,45	0	1	1249	9	0,91
3	210	1,00	0,69	0	1	1165	9	0,89
4	211	1,00	0,48	0	1	1518	9	0,92
5	213	1,00	0,92	0	1	1356	9	0,89
6	215	1,00	1,00	0	1	1434	8	0,75
7	216	1,00	0,97	0	1	1490	10	0,83
8	218	1,00	1,00	0	1	1556	8	0,70
9	219	1,00	1,00	0	1	1638	12	0,68
10	220	1,00	1,00	0	1	1629	8	0,68
11	221	1,00	0,95	0	1	1641	10	0,84
12	223	1,00	1,00	0	1	1697	8	0,68
13	224	1,00	0,98	0	1	1758	10	0,70
14	225	1,00	1,00	0	1	1801	8	0,67
15	226	1,00	0,91	0	1	1809	10	0,84
16	228	1,00	1,00	0	1	1840	8	0,67
17	229	1,00	0,97	0	1	1870	10	0,68
18	230	1,00	0,09	0	1	1848	12	0,55
:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:
644	9516	1,00	1,00	6	6	1568	6	0,69
645	9517	1,00	1,00	6	6	1569	8	0,67
646	9519	0,57	0,82	6	6	1589	10	0,47
647	9525	1,00	0,98	6	6	1766	12	0,07
648	9534	1,00	0,26	6	6	1912	11	0,39
649	9548	1,00	0,14	6	6	2240	12	0,66
650	9550	0,00	0,03	6	6	2012	10	0,54

Figure 7. Martix of performances. source([19])

B. *Identification of the decision makers*

The different decision-makers (actors) involved in the current study are:

- Decision maker 1: Environmental associations
- Decision maker 2: Politician
- Decision maker 3: Public.

A virtual cognitive agent, developed with the spade platform, represents each of these actors. To reflect the importance of the decision-makers in the decision-making process, a weight is assigned to each one of them using the AHP method. It's worth noting that since decision makers are deemed equal in importance, they are assigned similar weight ratings.

C. *Identification of decision makers' preferences*

Each decision maker must express their preferences in relation to the particular decision problem at hand. These preferences will be reflected in the formulation of the multicriteria method's subjective parameters. The first parameter is the weights of the criteria, which represent the relative importance of each criteria in relation to the others; these weights are determined using a multicriteria method called AHP; to do so, decision-makers must evaluate the criteria in pairs, using the Saaty scale [38] described in Table VII.

Table IX summarizes the three decision makers' judgments, whereas Figure 8 demonstrates the weights provided by the AHP method, which are reported in Table X.

TABLE VII. Saaty scale definition([38])

Rating scale	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgement slightly favor one element over another
5	Strong importance	Experience and judgement strongly favor one element over another
7	Very strong or demonstrated importance	An element is favored very strongly over another, its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is one of the highest possible order or affirmation
2,4,6,8	Intermediate values between the two adjacent judgement	When compromise is needed
$\frac{1}{x}$	Reciprocals of above	If activity i has one of the above nonzero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i

TABLE VIII. Cost/Benefit evaluations

	Harm	Noise	Impacts	Geotech	Equipment	Access	Climat
Evaluation	Max	Max	Max	Max	Max	Min	Max

Table VIII provides an assessment of cost/benefit for each criterion, with *"Max"* as a benefit criterion (the higher, the better) and *"Min"* as a cost criterion (the lower, the better). In the current study, thresholds of preference and indifference p_j and q_j on the criteria j, respectively, are chosen on the basis of values assigned to data uncertainties [19]. For example for an uncertainty of 20:

$$p_j = 2 * 20/100 * \max(j,k)[g_j(ak) - g_j(ai)] \tag{7}$$

$$q_j = 20/100 * \max(j,k)[g_j(ak) - g_j(ai)] \tag{8}$$

Where :

- $g_j(ai)$: The performance of action a_i according to criterion j.
- $g_j(ak)$: The performance of action a_k according to criterion j.

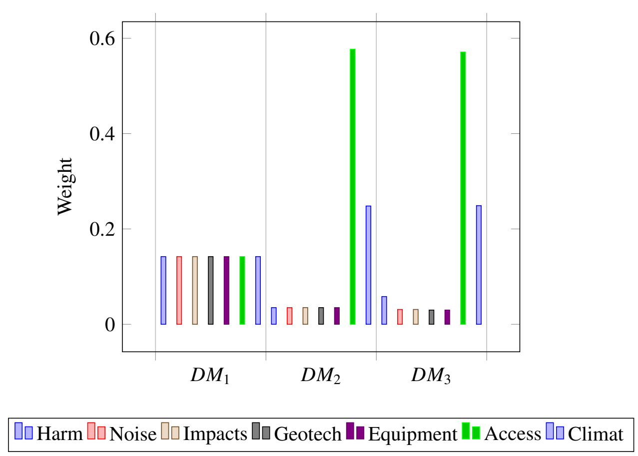


Figure 8. Criteria weights generated by AHP method

TABLE IX. Decision makers' linguistic preferences values

	Decision maker 1							**Decision maker 2**							**Decision maker 3**						
	Harm	Noise	Impacts	Geotech	Equip	Access	Climate	Harm	Noise	Impacts	Geotech	Equip	Access	Climate	Harm	Noise	Impacts	Geotech	Equip	Access	Climate
Harm	1	1	1	1	1	1	1	1	1	1	1	1	0.11	0.11	1	2	2	3	3	0.11	0.11
Noise	1	1	1	1	1	1	1	1	1	1	1	1	0.11	0.11	0.5	1	1	1	1	0.11	0.11
Impacts	1	1	1	1	1	1	1	1	1	1	1	1	0.11	0.11	0.5	1	1	1	1	0.11	0.11
Geotech	1	1	1	1	1	1	1	1	1	1	1	1	0.11	0.11	0.33	1	1	1	1	0.11	0.11
Equip	1	1	1	1	1	1	1	1	1	1	1	1	0.11	0.11	0.33	1	1	1	1	0.11	0.11
Access	1	1	1	1	1	1	1	9	9	9	9	9	1	9	9	9	9	9	9	1	9
Climate	1	1	1	1	1	1	1	9	9	9	9	9	0.11	1	9	9	9	9	9	0.11	1

TABLE X. Subjective parameters values

Decision Maker	Parameter	Harm	Noise	Impacts	Geotech	Equip	Access	Climate
Decision maker 1	Weight	0.14285714	0.14285714	0.14285714	0.14285714	0.14285714	0.14285714	0.14285714
	Consistency				True (index = 8.971499188890152e-16)			
	Preference Function	Linear	Linear	Linear	Linear	Linear	Linear	Linear
	Objective	Max	Max	Max	Max	Max	Min	Max
	Preference Threshold	0.0286	0.0286	0.0286	0.0286	0.0286	0.0286	0.0286
	Indifference Threshold	0.0571	0.0571	0.0571	0.0571	0.0571	0.0571	0.0571
Decision maker 2	Weight	0.034961676	0.034961676	0.034961676	0.03496167	0.03496167	0.57705986	0.24813175
	Consistency				True (index = 0.07529068111526545)			
	Preference Function	Linear	Linear	Linear	Linear	Linear	Linear	Linear
	Objective	Max	Max	Max	Max	Max	Min	Max
	Preference Threshold	0.007	0.007	0.007	0.007	0.007	0.1154	0.0496
	Indifference Threshold	0.014	0.014	0.014	0.014	0.014	0.2308	0.0993
Decision maker 3	Weight	0.05819457	0.03107063	0.03107063	0.02979537	0.02979537	0.57114848	0.24892491
	Consistency				True (index = 0.09567217164322203)			
	Preference Function	Linear	Linear	Linear	Linear	Linear	Linear	Linear
	Objective	Max	Max	Max	Max	Max	Min	Max
	Preference Threshold	0.0116	0.0062	0.0062	0.006	0.006	0.1142	0.0498
	Indifference Threshold	0.0233	0.0124	0.0124	0.0119	0.0119	0.2285	0.0996

D. Results and discussion

The authors provided WIM-GDSS with a set of panels that make the user comfortable with the different functionalities, and make the results clear for decision makers, for instance, Figure 9 illustrate the dashboard panel of each decision maker in the system. As illustrated, a menu is provided where the user can perform many tasks.

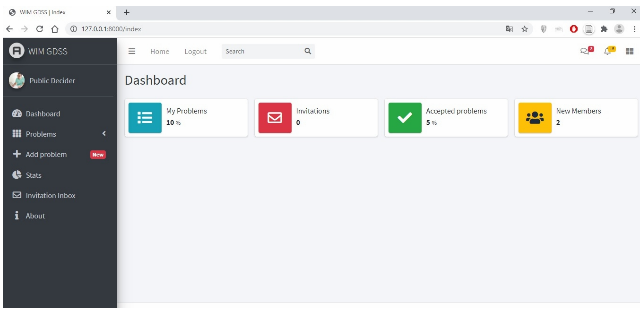


Figure 9. user dashboard page

As shown in figure 10, each agent has its own panel. The decision maker can also see the current position of his agent in the system, the messages exchanged, and the status of behaviors at any time.

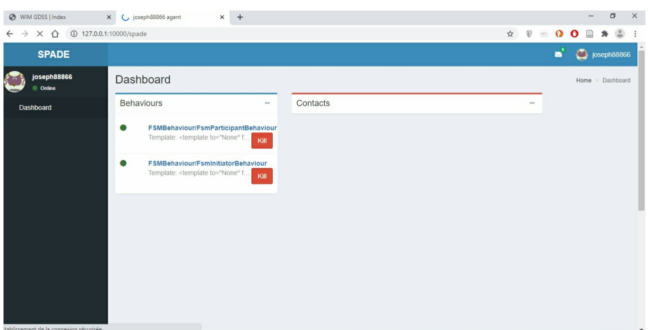


Figure 10. Spade agent web dashboard page

As stated above, each agent will either use a model (if it exist) or a PROMETHEE II method to determine the objectives vector of its corresponding decision maker and then sends the resulting vector to the initiator agent. The latter aggregate the vectors received from the agents involved, to form the group matrix of performances (GMP). After forming the GMP, the agent calculate the subjective parameters (see Eqs. (7) and (8)) and then check if a model is already trained for those parameters to predict the final solution, if not, the PROMETHEE II method is used to calculate the final scores and then a new model is trained and stored. The individual and global scores are illustrated in Table XI.

TABLE XI. Group decision matrix with global Netflows

Index	Id-zone	ϕ_1	ϕ_2	ϕ_3	$\phi_{Collective}$
		$w_1 = 0.33$	$w_2 = 0.33$	$w_3 = 0.33$	
1	202	-0,34102681	-0,06077011	-0,04286687	-0,43885639
2	209	-0,33240709	0,09053421	0,10682573	-0,1200641
3	210	-0,3082812	0,0882621	0,1037906	-0,12191834
4	211	-0,28104869	0,10652049	0,12101202	-0,06500154
5	213	-0,25938752	0,09792881	0,11215994	-0,07726903
⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮
648	9534	0,06490508	0,02514468	0,02269153	0,10043421
649	9548	0,25759476	0,28565131	0,28121217	0,77886009
650	9550	-0,12341803	-0,06198706	-0,08985485	-0,32411433

Individual and global final rankings of the alternatives constituting the group decision making problem are illustrated in Table XII. As shown in this table, the predicted rankings of some alternatives differ slightly from the computed rankings, which is due the the very small deviation between alternatives scores.

TABLE XII. Individual and group solutions

Rank	DM 1		DM 2		DM 3		Group Solution	
	Computed	Predicted	Computed	Predicted	Computed	Predicted	Computed	Predicted
1	1045	1045	3817	3817	3817	3817	**1045**	1045
2	5265	3817	1045	1045	1045	1045	**3817**	3817
3	1345	1345	3701	3701	3701	3701	**3820**	5265
4	4142	5265	3820	3820	3820	3820	**3822**	3820
5	3817	4142	845	1050	845	1049	**1049**	1345
6	1340	3822	1049	1049	1049	1050	**845**	3822
7	1343	3820	3822	845	1050	3822	**945**	945
8	1340	1343	1050	3822	3822	845	**5265**	745
9	745	6995	350	3401	350	3401	**1050**	1049
10	945	1340	349	6986	349	649	**745**	4142
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
648	8920	8920	8037	8037	7412	8037	**3289**	3289
649	2111	2113	7412	7412	7412	7412	**6020**	6020
650	2113	2111	9203	9203	9203	9203	**7412**	7412

Figure 11 illustrates the relationship between the decision-makers' scores (preferences) and the final (global) score. The upward-pointing lines imply a strong linear relationship (as the decision-score maker's increases, the global score increases as well).

E. Model selection

In machine learning, we usually select our final model after evaluating several candidate models.This process is called model selection[39]
The aim of this process, as with all machine learning scientists, is to find general patterns without getting trapped in overfitting and underfitting[39], The technique for selecting an appropriate model consists of selecting the model that performs best.
Because the goal is to predict values, the authors used a comparison analysis to compare two models, linear regression and multi-layer perceptron regressor, each with a different set of parameters.
Before training the models, the PROMETHEE II method was used to calculate the Netflows ϕ of each alternative. After that, link it to the dataset to create a labeled matrix, which is then fed to the model in order to train it to extract the desired patterns.
There were two scenarios envisioned :

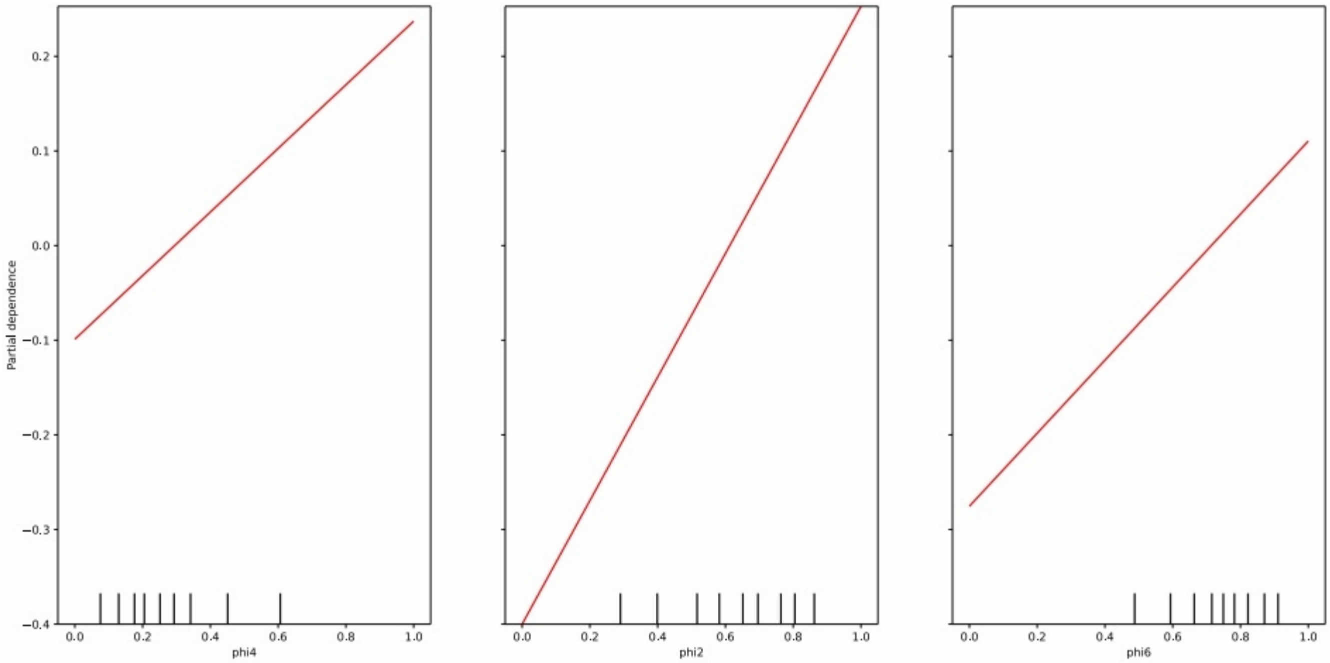


Figure 11. Partial dependence plots for group problem

- The first used the same preference functions for all of the criteria,
- The second used different preference functions.

It is important to note that preference functions apply to decision makers' actions against deviations between alternatives[29], or, the way of measuring the scores, so it is critical to see how the model performs under different circumstances. TableXIII depicts the models performances under the latter scenarios. As shown in the latter table

TABLE XIII. Linear regression vs Multi Layer Perceptron Regressor

	Linear regression	**Multi-layer perceptron**
1^{st} **scenario**	96 %	99 %
2^{nd} **scenario**	72 %	95 %

and Figure 12, the accuracy of the linear regression model decreased significantly in the second scenario (from 96 percent to 72 percent). It is noticeable from Figure 13 the significant shift in alternative ordering which is inadequate. On the other hand, the accuracy of the MLP regressor model has decreased slightly (from 99 percent to 95 percent), but it is still permissible.
For the reasons mentioned above, the authors chose to use the MLP model in this version of WIM-GDSS.

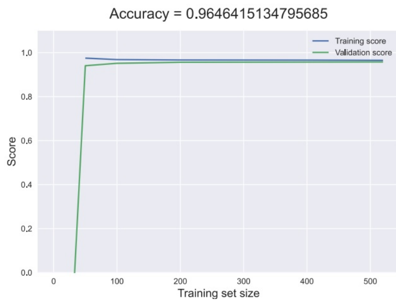
Table XIV shows the MLP model's parameters that provide the best results.

TABLE XIV. MLPR characteristics

Parameter	Value
Architecture	3-layer perceptron fully interconnected Neurons (MLP).
Hidden layers	1 layer
Number of neurons	7 neuron input layer; 100 neurons hidden layer; 1 neuron output layer
Activation function	RELU (Rectified Linear Unit)
Solver	LBFGS (Limited-memory Broyden–Fletcher–Goldfarb–Shanno)
Input layer	Criteria
Output layer	Alternative predicted score

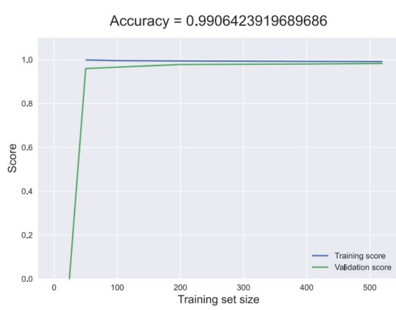
F. Results interpretation

The authors plotted the partial dependencies plots shown in figures 14, 15 to interpret the model decrease in the second scenario. The latter plots depict the relationships between the criteria and the final score extracted by the models; it is clear that all of the relationships extracted by the linear regression model are linear, whereas the MLP extracted non-linear relationships for some criteria.



(a) RL : Scenario 1

(b) RL : Scenario 2



(c) MLP : Scenario 1

(d) MLP : Scenario 2

Figure 12. learning curves RL vs MLP

ID_ZONE	SCORE
9517	0.36512542
5529	0.35885716
8365	0.35772989
8352	0.35689954
1323	0.35585778
4174	0.35382296
4190	0.35314222
1320	0.35254068
9516	0.35006795
4168	0.34733867
2723	0.34502481
5538	0.34049091
4167	0.33915732
5542	0.33914037
4169	0.33674422
2719	0.33583097
2718	0.33316317
1312	0.32679492
6668	0.32030447
2710	0.3164037
1237	0.309253
2706	0.307898

(a) PROMETHEE ranking

ID_ZONE	SCORE
2745	0.74776903
5558	0.74000169
9550	0.73968336
4153	0.72743775
2725	0.72037643
2713	0.70857396
2749	0.69776672
4150	0.68471079
2744	0.68091063
2715	0.6522077
5258	0.63732018
2711	0.63613975
9250	0.63500786
2712	0.62086071
8069	0.61964761
2444	0.61951279
2449	0.61800139
9450	0.60802435
1006	0.57852573
706	0.57337103
2113	0.55804854
8920	0.55710693

(b) Model ranking

Figure 13. Linear regression vs PROMETHEE rankings of the second scenario

The plotted results provide an interpretation of why the linear regression model did not perform well in the second scenario, which is due to the non-linear relationships between the inputs and outputs, whereas the MLP, known for its ability to extract such relations, provides a high satisfying accuracy.

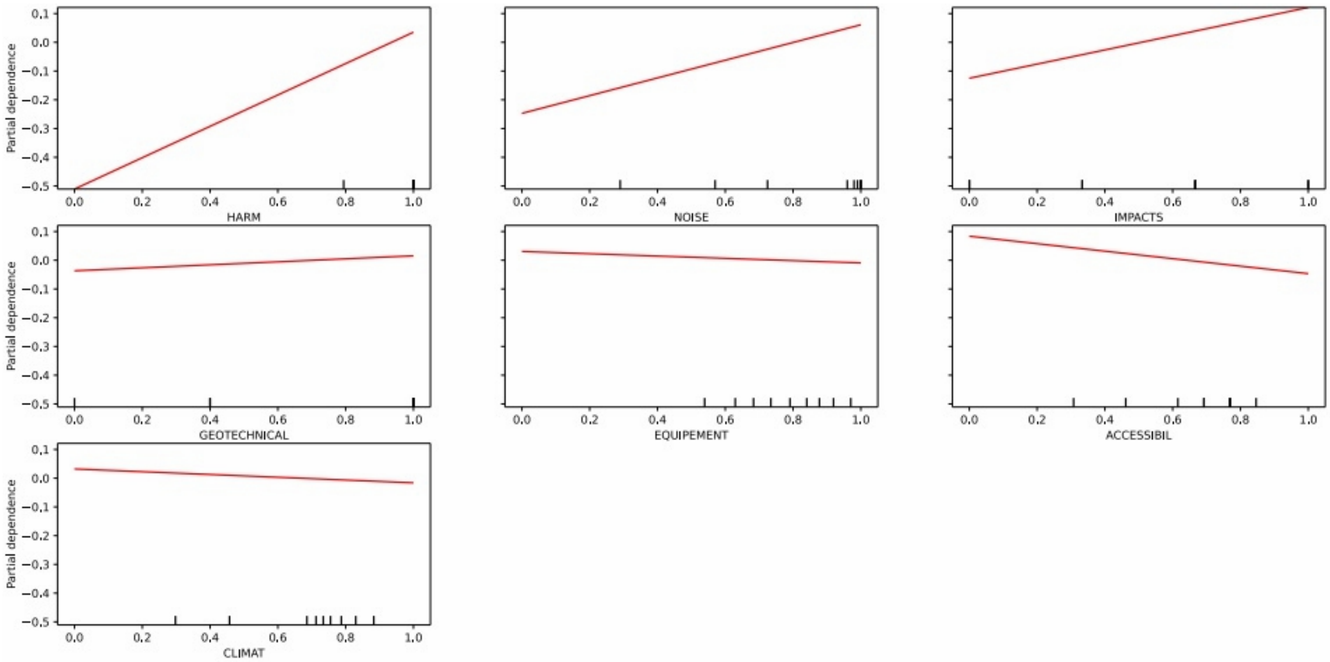


Figure 14. Partial dependence plots for linear regression model

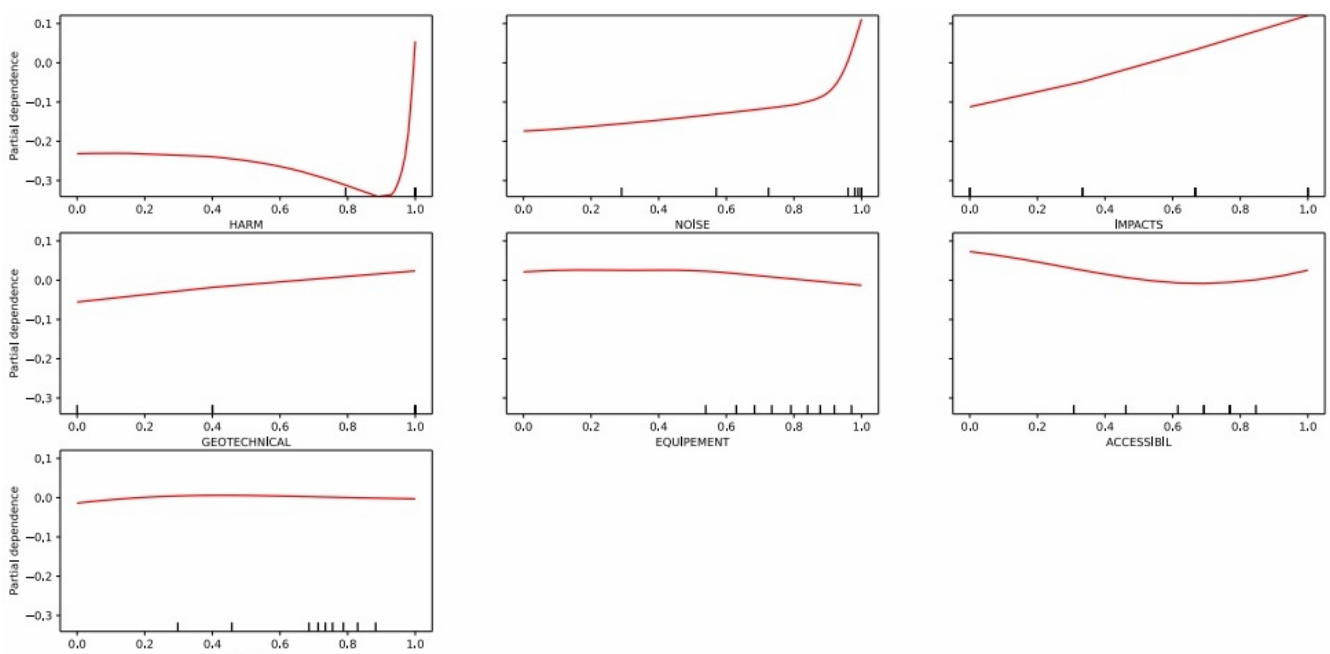


Figure 15. Partial dependence plots MLP regressor model

6. Conclusion and future work

A Web Intelligent multicriteria Group Decision Support System (WIM-GDSS) for Land Use Management was proposed in this paper. Multi-agent system, geographic information system, multiple criteria decision support, and artificial intelligence are all included in the latter. This system is designed to deal with issues involving numerous decision-makers with competing interests who are affected by a variety of factors. To ensure a distributed environment, the decision-makers in WIM-GDSS are modeled by virtual cognitive agents using a multi-agent system, allowing the decision-makers to coordinate for choosing the alternative that best meets the given criteria. The latter agents have the ability to predict the desired outcome while taking into account the preferences of the decision makers. They can also train new models based on the results of the multicriteria analysis methods (PROMETHEE II) and store them for future use. To choose the adequate prediction model, a comparison analysis was conducted between linear regression and multi layer perceptron models, the main objective of the selected model is to predict the outcome of PROMETHEE II method for a given problem, The results obtained suggested that the MLP model is better with an accuracy of 95% compared to 72% for LR model. This paper's work, like any other research work, has limitations, and we look forward to exploring some of these limitations in order to develop a better version of WIM-GDSS.
The following are some perspectives that we hope to resolve in the future:

- Integrate the GIS tool completely into WIM-GDSS
- To tackle data uncertainties in the multicriteria module, use fuzzy multicriteria methods
- Optimize the proposed model to reduce the number of new trained models
- In the prediction module, trains unsupervised models.

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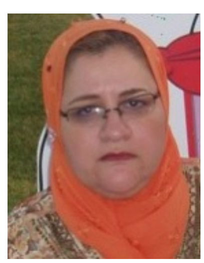

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