eMediation
Towards Smart Online Dispute Resolution

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Abstract: In this paper, the main requirements towards the next generation of Smart Online Dispute Resolution Systems for eMediation are presented and addressed through the definition of an advanced computational intelligence framework. The main contributions can be distinguished with respect to the parties involved in the eMediation process. Concerning the disputants, the main advancements are related to a smart data collection environment to state the essence of the litigation and an intelligent retrieval of court decisions to improve the awareness of the parties about their liability. Regarding the role of the mediator, the essential point addressed relates to an estimation of disputant flexibility to facilitate the optimal mediation strategies.

1 INTRODUCTION

The increasing workload of civil justice courts is encouraging the adoption of novel litigation support systems. A recent EU Directive[1] highlights the importance of facilitating access to Alternative Dispute Resolution (proceedings with no formal court hearing), to promote the amicable settlement of disputes by encouraging the use of ADR and ensuring a balanced relationship between ADR and judicial procedures. In order to understand the role that ICT could play in settlement of conflicts, we report the numbers of Alternative Dispute Resolution (ADR) cases addressed at European level. According to the 2011 report disclosed by the EU Parliament the increasing trend in the use of ADR counts about 410.000 cases in 2006, 473.000 in 2007 and more than 500.000 in 2008. More impressive numbers are related to the Italian context, with a particular focus on mediation (one of the available schemas for ADR). According to the statistics provided by the Italian Ministry of Justice, about 231.500 cases have been addressed through ADR between March 2011 and September 2013. Italy's Central Bank has estimated 16 billion euro loss in terms of GDP caused by the slow of civil justice, highlighting the needs of encouraging alternative resolutions of disputes both from citizen and "justice system" points of view. The comparison of Italian *in* and *out* of court civil proceedings - average trial duration of 1066 days versus 65 days time limit for mediation - makes clear the role that ICT could play to shift from ADR to ODR (Online Dispute Resolution), where technology could facilitate and speed up the resolution of disputes. Several commercial initiatives, mainly focused on Internet-based support toolsets, have been introduced to enable ODR, while the research initiatives are mainly focused on advanced reasoning mechanisms to facilitate the resolution of the disputes under a specific negotiation schema. A first example of computational negotiation system is represented by DEUS (Zeleznikow et al., 1995) that, receiving as input specific goals and beliefs of litigants, computes the agreement level in family law property negotiations. More sophisticated systems are represented by Split-Up (Zeleznikow and Stranieri, 1995) and Family-Winner (Bellucci and Zeleznikow, 2001). Split-Up is a hybrid framework that combines rule-based systems and neural networks to assist disputes about properties distribution. Family-Winner, which is a game theory-based approach for Australian family negotiations, asks disputants to list the items involved in the litigation and to assign a corresponding relevance value. The system formulates an influence diagrams to subsequently use game theory to determine a suitable trade-off between claims. Moreover, the BEST-project (Uijttenbroek et al., 2008) provides ontology-based search of law cases to allow parties the opportunity to evaluate claims and liabilities. (For

[1]2008/52/EC of 21st May 2008

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a review on commercial and research initiatives for ODR refer to (Carneiro et al., 2014)). The results obtained by the above mentioned investigations are mainly related to negotiation as a form of dispute resolution. To the best of our knowledge, until now no contribution has been given with respect to mediation as an alternative schema for *out* of court disputes. In this paper, the main requirements towards the next generation of Smart ODR Systems for eMediation are presented and addressed through the definition of a computational framework based on advanced artificial intelligence methodologies.

2 TOWARDS SMART ODR SYSTEMS

The spread of mediation through a next generation of ODR systems, is dependent on the suitable exploitation of communication technologies coupled with advanced computational intelligence approaches such as knowledge management, machine learning, information retrieval and operational research. The requirements towards an effective support to eMediation by Smart ODR Systems should take into account the needs both disputants and mediators. Concerning the disputants involved in a litigation, the essential requirements are (1) a smart data collection functionality to state the essence of the litigation and (2) an effective retrieval system of court decisions to improve the awareness of the parties about their BATNA[2] and WATNA[3]. Regarding the role of mediator, the main desiderata relates to (3) the possibility of estimating the flexibility of the parties to be guided through a set of mediation strategies to likely settle an agreement.

Smart Data Collection. A Smart ODR System should enable the acquisition of information about the citizen's case. An intuitive support to the collection of case characteristics is compulsory for enabling any decision process, both from disputant and mediator points of view. If we focus on the state of the art related to ODR, we can easily point out that claims and requirements are typically collected by a fixed-structure template to be filled in by parties, with no possibility to provide argumentations by using natural language. In this context, a fundamental role is played by those mechanisms able to acquire information from the parties by following an intuitive data collection process. A smart assistant able to guide the disputants to provide the right information about their case represents a crucial leverage to enable either "artificial" or "human" reasoning mechanism concerned with ODR. In particular, a proper acquisition of the case description could improve the retrieval of court decisions related to a given case for helping the disputant in better understanding his/her position: of rights and duties, chances in a potential in-court litigation, time and costs, and so on. Moreover, it could also help the mediators for better understanding the case, for instance by providing a summary of questions and answers that characterize the case itself. In order to match this requirement, a smart data collection based on knowledge needs to be introduced in the next generation of Smart ODR systems.

Improving Awareness of the Parties. From the disputant point of view, once a proper acquisition of user claims and requirements has been performed, the first step towards a Smart ODR System is represented by the well-known BATNA and WATNA concepts of principled negotiation (Fisher et al., 2011). In fact, crucial requirements for enabling the adoption of ODR systems are (1) the natural language argumentation of claims and requests related to the citizens case and (2) the possibility to gain knowledge by easily accessing and consulting former court decisions related to similar disputes. Indeed, glancing at similar cases to understand rights and duties, relevant norms, times and costs of potential in-court-proceedings and prospective outcomes of the dispute may increase the awareness of the disputant. Providing information about the party legal positions could help to improve the awareness about their own liability and to figure out their chances in court proceedings (usually overestimated). Therefore, Smart ODR Systems should provide a retrieval functionality able to bring the gap between the layman case description and the court decisions.

Enhancing the Flexibility of Parties. If we focus on the mediator needs, the main requirement towards Smart eMediation Systems relates to the evaluation and the improvement of the flexibility of the disputants involved in a conflict. Improve this flexibility could increase the possibility to settle an agreement when critical situations occur. The flexibility of a dispute, which mainly depends on the propensity of the parties to achieve an agreement, is a key aspect that a mediator should evaluate after the first meeting with the parties. When a critical situation occurs, i.e.when the party's flexibility is low or large asymmetries are detected, resolution strategies should be suggested to the mediator for improving the possibility to achieve an agreement among parties. This could help mediators to enhance the flexibility of the parties by analyz-

[2] Best Alternative To a Negotiation Agreement, i.e. the best option a party has if negotiation fails

[3] Worst Alternative To a Negotiation Agreement, i.e. the worst option a party has if a resolution cannot be reached

ing the initial state of a mediation and detecting critical situations a-priori. The possibility of comparing different what-if scenarios could help in the planning of further meeting and in deciding what strategies to apply in a particular scenario. Moreover, the system could also be used as learning environment in which hypothesize and compare different real situations or toy examples, analyze flexibility evaluation and compare suggested strategies.

These requirements have converged in the **eJRM** project, acronym of **e**lectronic **J**ustice **R**elationship **M**anagement , which represents an ongoing Italian initiative aimed at improving the awareness of citizens to personally evaluate the outcome of a potential litigation and to be guided to a non-conflict settlement. In particular, the above mentioned requirements have been addressed to allow a radical improvement of two major processes:

- **eMediation:** online management of activities related to the mediation process
- **Self-Litigation:** capability of a citizen to autonomously classify, formalize and understand the potential outcome of a dispute

In the following sections, the main contributions towards a Smart ODR for eMediation are detailed.

3 ONTOLOGY-DRIVEN DATA ACQUISITION

An interactive and self-administered interviewing system has been designed in order to collect useful information for enabling either eMediation or Self Litigation processes (Arosio et al., 2013). Disputants respond to a sequence of questions on their specific case: the system selects pertinent questions depending on the disputants's individual responses. Upon completion, a summary is presented to the parties. The interview system, based on specific domain knowledge, helps both disputants and mediator to save time, offers a database for retrieval functionalities, and provides only relevant information related to the conflict. The Ontology-driven Data Acquisition system (ODA) is composed of two main parts: (1) an ontological structure aimed at modeling the juridical knowledge related to a specific application domain and (2) a logical engine targeted at exploring the ontological structure in order to provide questions and collect responses to/from the disputant.

3.1 Ontological Structure

The ontological structure underlying ODA formalizes the concepts to be acquired from the user by presenting a set of interrelated questions. Basically, concepts and relationships have been designed in order to represent a smart question-answering flow, by modeling yes/no questions, multiple-choice questions as well as the potential correspondence between answers and violation of specific norms. *Questions*, *Responses* and *Norms* (applicable rules and violated norms) have been modeled as schema concepts (`owl:Class`), while the individuals - that can belong to only one of the three concepts - are acquired via questions presented to the user. Whenever a given norm is violated, the system presents the text of the corresponding norm for consultation purposes.

The relationships (predicates) designed in the ontological structure link couples of concepts in order to represent the whole question flow presented to the user. The considered predicates (`owl:objectProperty`) are listed below:

- *assume*: relationship that links two concepts such that the domain concept is verified if and only if the co-domain concept has been already acquired during the interview;
- *assumeAND*: relationship that links a concept to multiple concepts such that the domain concept is verified if and only if all the co-domain concepts have been already acquired during the interview;
- *assumeEXCL*: relationship that links a concept to multiple concepts such that the domain concept is verified if and only if only one of the co-domain concepts has been previously acquired;
- *assumeOR*: a relationship that links a multiple-choice question concept with all its own answer concepts;

Between questions and norms, two kinds of relationships have been modeled, a *violatedWhen* relationship that links a norm to a question that could lead to its violation and a *verifiedWhen* relationship linking a norm to a question that could lead to its compliance. The modeling of knowledge to be included in the ontological structure relates to specific domains, but it does not require a tedious and often unfeasible top-down approaches for representing the whole domain considered. The modelling criteria are indeed generic and can be in principle applied to any judicial domain. In our investigation, locations, taxes and tributes, and civil liability related to the use of motor vehicles have been modeled as case studies.

3.2 Logical Engine

In order to explore the ontological structure as defined in the previous subsection, we have defined a logical engine able to provide a context-sensitive adaptive questionnaire. The logical engine has two main goals: (1) to explore the ontology in order to gather concepts to be characterized by the disputant and (2) to show to the user the question related to the given concept and to acquire his/her response. Concepts modeled within the ontological structure represent relevant information to be acquired in order to characterize a disputant's case. Each concept is therefore directly connected with the corresponding question to be presented to the user. In order to provide a mechanism able to firstly explore the ontological structure and consequently manage questions/answers, we designed a logical engine based on the "Last State-Next State" model (LSNS) (Bouamrane et al., 2008). According to this model, a given concept to be acquired (what question is currently processed) could lead to several potential subsequent concepts to be explored (the next question given the user's response). The proposed logical engine implements a short-term memory approach based on predicate priorities. This allows us to provide questions related to a given concept only if prerequisite concepts have been previously verified (according to their ontological properties). This logical engine makes it possible to disregard long-term dependencies among the concepts underlying the ontology questionnaire and to be independent on the juridical domain modeled. The system makes also available the consultation of the norms (both applicable and violated) according to the disputant's responses, enabling therefore a better understanding of rights and duties. The main advantage of the proposed systems, both for disputants and mediators, is the reduction of time in respect of the a simple conditional branching questionnaire. Moreover, ODA system helps disputants to autonomously classify, formalize and understand the potential outcome of a litigation, as well as mediator to save time and to avoid biases and errors when collecting the interview's responses.

4 MACHINE LEARNING BASED RETRIEVAL

In order to improve the awareness of the parties involved in a eMediation, a retrieval functionality needs to be designed to support the disputants in glancing court decisions that could potentially be related to their own case description. The main issues that a retrieval functionality should address relates to the nature of the language, i.e. formal and verbose for court decisions and informal and concise for the conflict description provided by the disputants. In order to deal with this issue, a Machine Learning based Retrieval has been defined. The main functionalities of this component are:

1. *Indexing:* is the first step for processing the court decisions documents in order to create a structured representation as *bag-of-words*. First of all, stop-words, digital numbers and separator characters are removed. Therefore, a stemming is applied to the resulting terms in order to reduce the size of the *terms dictionary*[4] and thus to prevent a potential over-fitting phenomenon.
2. *Core Mining:* the goal of this functionality is to associate a main topic (e.g., Damage, Family, Failure of business, Divorce, etc...) to a disputant description. First, court decisions are represented according to the bag-of-words models (Salton et al., 1975) and the TF-IDF scoring technique (Salton and Buckley, 1988). Considering that the bag-of-words representation is characterized by a huge number of attributes (terms) that could affect the prediction of the topic related to a given dispute description, a dimensionality reduction has been enclosed. In particular, Principal Component Analysis has been adopted to reduce the dimension of the bag-of-words representation. Generally, 98% of terms are reduced without losing the relevant information, that allows to build a classification machines in an efficient manner. Once a proper representation has been derived for court decision documents, several machine learning classifiers (Support Vector Machine, Naive Bayes and Tree Decision) have been trained to derive a model able to pr capture the topic related to a dispute description.
3. *Query Processing:* Before providing the dispute description to the Core Mining functionality, the corresponding text has been tokenized and preprocessed. The output is a vector of terms that has the same dimension of the term dictionary (the terms extracted from the user query that do not match the terms dictionary are ignored).
4. *Ranking:* It computes the similarity between the disputant case description and the court decision documents corresponding the topic predicted by the Core Mining functionality. Then, it ranks the similarity scores in a descendant order to finally

[4]The *terms dictionary* is the list of terms shared among court decisions

provide the top ten court decisions to the disputant. In order to address the issue related to the language difference between the court decision documents and the disputant query, two main contributions have been provided:

- Term Evaluation and Selection (TES), to better identify the terms that characterize a given topic (e.g. *vehicle* for the topic *Car Accident*)
- Zipf-based Similarity Measure (ZSM), to better capture the similarity of the natural language used both in court decisions and disputant query.

TES is based on two criterions for detecting the Relevant Terms (RTs) from the court decision document collection: the percentage of term frequency per class (ptfc) and the term presence per each class. If a term is omni-present in a class (high value of *pftc*), the term will be a RT, otherwise it will be disregarded. RTs are then used to train classifiers and to predict the most probable topic of a given disputant case description. Once a topic has been associated to the disputant case description, the most relevant court decisions are determined according to the ZSM. To this purpose, court decisions and dispute description have been represented by using power law distributions that reflect the Zipf's Law underlying the natural language. Once the Zipf distributions have been derived, ZSM can applied: term frequencies that are close to the mean of the distributions (i.e. the most important terms) contribute more in the similarity computation, while either rare or common terms have a reduced impact. ZSM allows us to tackle the retrieval problem for eMediation processes: ZMS is able to addresses different kind of languages, i.e. lengthy for court decisions while condensed for the conflict description provided by the disputants.

5 FLEXIBILITY-BASED RESOLUTION ASSISTANT TO eMEdiations

In the context of eMediation, at our knowledge, **F**lexibility-based **R**esolution **A**ssistant to e**ME**diations (FRAME) represents the first attempt to quantitatively model qualitative aspects that mediators usually consider in the management of a mediation: during the first fact-finding meeting, mediators evaluate the initial state of the mediation, in order to understand how to conduct the further meetings with the disputants with the scope to solve the conflict. The evaluation of the dispute and the decisions about the actions to be taken to likely achieve an agreement are performed by mediators in an implicit way. This process is mainly related to the experience of the mediator itself. Starting from this consideration, the main scope of FRAME is to model elements considered by mediators in evaluating and conducting the mediation process: in order to achieve this aim, and to understand which aspects are actually relevant, different interviews with a domain expert (i.e. a mediator with more than 20 years of experience in the mediation field) were conducted in order to acquire all the relevant information in this context. These knowledge acquisition sessions produce as output a representation of the mediator mental process in terms of factors that characterize the mediation and determine its possibility to reach a positive solution, and a set of strategies/mechanisms that the experts can apply in order to solve critical situations.

In order to match the requirements introduced in section 2 and to help mediators in the management of their disputes, we have developed FRAME taking into account all the information acquired during the interviews with the domain expert. FRAME is a web-based Java application, composed of two parts: the first one relates to the evaluation of a mediation in terms of flexibility values associated to the disputants involved, and the second one relates to the suggestion of strategies/mechanisms to be applied to likely achieve an agreement among parties. In the next sections, the two components will be discussed.

5.1 Flexibility Evaluation

A value of flexibility, which represents the disputant's positive aptitude to achieve an agreement, can be associated to each litigant[5]. According to the knowledge acquired from the domain expert, a set of relevant *factors* that could be observed in the case of Italian mediation have been identified. These factors have been used to create a fixed-structure questionnaire to be compiled by the mediator after the first meeting with the disputants, where each multiple-choice question is modeled to acquire the value of a given factor as positive or negative. We define F as the set of factors that influences the resolution of a mediation. We identify three categories of factors, such that $F = Fm \cup Fd \cup Fp$:

- $F^m = \{f_1^m, \dots, f_\alpha^m\}$, set of factors that characterize the *mediation* in terms of the full process, such as the kind of mediation, the type of mediation

[5] An impasse or a critical situation are mainly due to low levels of flexibility and/or large asymmetry between the disputant flexibility.

opening demand, the presence of an expert in the dispute domain, and so on;

- $F^d = \{f_1^d, \ldots, f_\beta^d\}$, set of factors that characterize the *dispute*, such as the economic value, the level of complexity, the overall level of conflict and so on;
- $F^p = \{f_1^p, \ldots, f_\gamma^p\}$, set of factors that characterize the *parties* involved in the mediation, such as their attitude toward the mediation process, their behavior with respect to the mediator and to the other parties, their necessity to close the dispute and so on.

Inspired by the work of Druckman (Druckman et al., 2002; Druckman et al., 2004), the overall flexibility associated to a disputant h has been defined as:

$$Flex(h) = \sum_{i=1}^{|F^m|} f_i^m w_i v_{i,h} + \sum_{j=1}^{|F^p|} f_j^p w_j v_{j,h} + \sum_{k=1}^{|F^p|} fp_k w_k v_{k,h}$$

where $w_\zeta \in [0,1]$ denotes the relevance weight of each factor $f \in F$ and $v_{\zeta,h}$ represents an estimate provided by the mediator to a given factor with respect to the given dispute. The variable $v_{\zeta,h}$ takes values into the continuous interval $[1,4]$, where $v_{\zeta,h} \in [1-2]$ means a negative evaluation of the factor while $v_{\zeta,h} \in [3-4]$ a positive one. For seek of simplicity, let's assume a mediation with two parties. In this case, the questionnaire is composed of a total of 54 questions (the values between brackets represent the estimate $v_{\zeta,h}$ provided by the mediator to a given factor with respect to the given dispute):

- *Mediation* factors $[F^m]$ (8 questions):
  - **[M1]** type of mediation: voluntary (4) - stated by contract (3) - court ordered (2) - compulsory (1);
  - **[M2]** type of instance: joint (4) - ordinary (2);
  - **[M3]** information of the mediation instance: complete (4) - incomplete (1);
  - **[M4]** information to the disputants: complete (4) - incomplete (1);
  - **[M5]** disclosure: yes (4) - no(1);
  - **[M6]** expert involved: yes (4) - no (1);
  - **[M7]** confidentiality: reserved (4) - public (1);
  - **[M8]** relationship among disputants: amicable (4) - good natured (3) - neutral (2) - hostile (1);
- *Dispute* factors $[F^d]$ (6 questions):
  - **[D1]** level of divergence among parties: no conflict (4) - weakly conflictual (3) - slightly conflictual (2) - strongly conflictual (1);
  - **[D2]** third parties involved: yes (4) - no (1);
  - **[D3]** economic value of the dispute: up to 50k euro (4) - from 50k to 100k euro (3) - from 100k to 250k euro - above 250k euro;
  - **[D4]** complexity of the dispute: easy (4) - weakly complex (3) - slightly complex (2) - strongly complex (1);
  - **[D5]** number of elements that can leverage the parties to settle an agreement: high number (4) - medium number (3) - sufficient number (2) - scarce number (1);
  - **[D6]** experience required to the mediator: low (4) - medium (3) - high (2) - very high (1);
- *Parties* factors $[F^p]$ (20 questions):
  - **[P1]** mediation professional body: selected by the disputant (4) - non selected by the disputant (1) - no mediation instance (4);
  - **[P2]** joint judicial instance: yes (4) - no (1);
  - **[P3]** time needs to close the dispute: high (4) - medium (3) - low (2) - no time limits (1);
  - **[P4]** costs needs to close the dispute: high (4) - medium (3) - low (2) - no time limits (1);
  - **[P5]** type of disputant: natural person (4) - legal representative (1);
  - **[P6]** type of lawyers: lawyer and mediator (4) - lawyer (1);
  - **[P7]** lawyer predisposition: collaborative (4) - positive (3) - indifferent (2) - uncooperative (1);
  - **[P8]** disputant objective vision: high (4) - medium (3) - low (2) - no objective vision (1);
  - **[P9]** understanding of the other disputant position: total (4) - partial (3) - sufficient (2) - no understanding (1);
  - **[P10]** previous relationships among parties: previous relationships (4) - no former relationships (1);
  - **[P11]** possibility of future relationships among disputants: high (4) - medium (3) - low (2) - no possibility (1);
  - **[P12]** socio-cultural aspect: equal (4) - higher than the other (2) - lower than the other (2) - very high/low than the other (1);
  - **[P13]** level of education: equal (4) - higher than the other (2) - lower than the other (2) - very high/low than the other (1);
  - **[P14]** level of psychological intimidation: no intimidation (4) - weakly intimidated (3) - slightly intimidated (2) - strongly intimidated (1);
  - **[P15]** emotional involvement: no involvement (4) - weakly involved (3) - slightly involved (2) - strongly involved (1);

- **[P16]** conflict of disputant: high (4) - medium (3) - low (2) - no conflict (1);
- **[P17]** linguistic register: clear (4) - vague (1);
- **[P18]** linguistic/gesture: friendly (4) - aggressive (1);
- **[P19]** listening availability: high (4) - medium (3) - low (2) - no availability (1);
- **[P20]** behavior during the meeting: friendly (4) - sully (1);

Once the questionnaire has been filled in by the mediator, the partial flexibility for each factor set (i.e. F^m, F^d and F^p) is computed and the final flexibility $Flex(h)$ is estimated for each disputant involved in the conflict. Flexibility values are then displayed to the mediator and graphically shown in a Cartesian diagram displayed as a grid (see Figure 1). Cells C and E represent agreement among parties, in particular joint maximum flexibility in cell C and joint moderate flexibility in E. Asymmetrical flexibility can be identified in cells A and I. The remaining cells represent no agreement among parties, with cell G indicating joint intransigence or no movement. Figure 1 shows an example of the flexibility graphical representation, in which a large asymmetry between the two parties can be easily detected: party 1 (blue line) and party 2 (green line) have a flexibility value equal to 37.1% and 65.28%, respectively. The intersection, represented as a red point, provides a first qualitative evaluation of the state of the mediation.

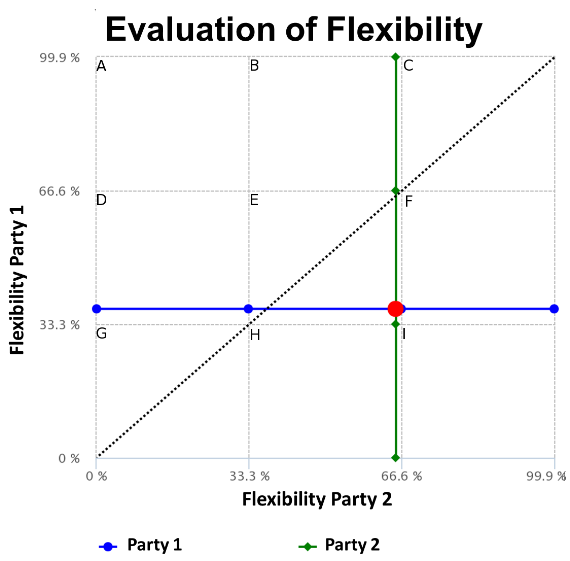

Figure 1: Graphical representation of party 1 (blue line) and party 2 (green line) flexibility: the red point indicates the intersection between the two flexibility lines and provides a qualitative evaluation of the state of the mediation.

In the example above the state of the mediation (red point) denotes a potential agreement among parties (cell E) but with a quite large asymmetry (red point far from the bisector). The best case appears when the intersection of flexibility lines lies on the top-right quadrant (cell C) and near to the bisector axis (i.e. the two values of flexibility are enough high and there is no asymmetry). Differently, when the intersection lies in the other quadrants and/or far from the bisector axis, the mediation can present critical situations of impasse or low levels of flexibility for one or for both parties. The evaluation of flexibility provided by FRAME is a first contribution towards Smart ODR Systems for eMediation, which not only helps the mediators to understand critical situations but also to clearly state the factors (mediation, conflict and parties) that partially affect the settlement of agreements. After the flexibility evaluation, the mediator can choose to start an analysis of the initial situation, in order to automatically identify critical situations and obtain suggestions related to which strategies and mechanisms can be used in case of low values of flexibility or asymmetries.

5.2 Strategy Suggestion

An analysis on the state of the art of the mediation management (Danovi and Ferraris, 2013; Bush and Folger, 2004) has revealed that some mechanisms and strategies exist and can be applied to improve the flexibility of the disputants and to solve asymmetries. To this purpose, a set of strategies has been identified as potential leverage that could have positive impact on some factors and therefore improve the overall flexibility. More in detail, we have defined a set of strategies $S = \{s_1, \ldots, s_r\}$ where each s_l has a cost $c_l \in [0,1]$ and a probability $g_l \in [0,1]$ to solve a given subset of factors. Each strategy can be applied to improve the value of some factors $f \in F$ when they are evaluated as negative by the mediator answering to the questionnaire (i.e., when factors takes values among 1 and 2 in the evaluation process). The strategies identified by the domain expert are reported in the following:

- *communication* to improve and manage the communication between the disputants;
- *focus on mediation principles* to recall the disputants the mediation purposes and benefits;
- *containment* to smooth the contraposition between disputants;
- *active listening* to bring a disputant towards the understanding of the other litigant empathy;
- *empowerment* to make disputants more confident in rights and duties;

- *improve the mediator authoritativeness* to make disputants more confident in the mediator;
- *entailment of lawyers* to involve more lawyers and therefore parties;
- *search of the substantial leader* to improve his/her involvement into the mediation;
- *search of information* to discover additional documents and objective evaluations;
- *interests finding* to discover emotional aspects that can be used to understand and solve the dispute;
- *brainstorming* free discussion about the dispute that could enable novel and original solutions;
- *involvement of experts* to collect additional information and evaluation about the dispute;
- *private meetings* with disputant and lawyer to discover additional (private) information;
- *reality test* to allow parties to understand real and objective needs.

FRAME performs a two-phase analysis to find the set of strategies to be proposed to the mediator to improve the chance to find an agreement: the first step consists in the analysis of the collected answers, in order to identify the factors that have been indicated as negative by the mediator. A set of the potentially applicable strategies is then inferred by means of an expert system based on JESS rule-based engine[6]. After the identification of this preliminary set, a refinement is produced by solving an integer linear programming problem in order to find the optimal set of strategies to be applied. The goal is to propose to the mediator only the strategies that (i) minimize the effort of the mediator and that (ii) maximize the value of flexibility of the party (under the constraint to limit the asymmetry between the two parties). The identification of the optimal set of strategies to be applied considers two main aspects: (1) the cost $c_l \in [0,1]$ of each strategy, i.e. the difficulty for a mediator to apply a given technique, and the corresponding probability $g_l \in [0,1]$, i.e. how likely a strategy can solve the related factors. Once the optimal set of strategies has been determined, it is provided to the mediator in order to improve the chances to achieve an agreement.

6 CONCLUSIONS

The diffusion of both ADR and ODR has become a significant factor in instilling confidence in the legal framework as a whole, supporting and promoting the rule of law. In this paper, the main requirements towards Smart Online Dispute Resolution for eMediation has been discussed. As a consequence, a computational intelligent system has been proposed to address (1) a smart data collection to state the essence of the litigation, (2) an intelligent retrieval of court decisions to improve the awareness of the parties about their liability and (3) an estimation of disputant flexibility for the subsequent identification of optimal mediation strategies to achieve an agreement among parties. This work represents a first initiative towards smart mediation that could be used as roadmap for the next generation of intelligent eMediation systems.

[6]http://herzberg.ca.sandia.gov/

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