Dispute Resolution with Arguments over Milestones:
Changing the Representation to Facilitate Changing the Focus

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ABSTRACT

We propose improving the language of dispute resolution (whether online, ODR, or alternative, ADR) by importing a new representation that was designed for use in hybrid analyses that combine decision, risk, and constructive argument.

This representation was designed to push back against short horizons and narrow focus, by making the proposed plan, or trajectory, diachronically explicit, dynamically extensible, and potentially qualitative. Probability is used in a novel way, to guarantee transition from one milestone to the next, rather than to discount utility valuation. Arguments more easily occur over joint problem solving to provide stronger guarantees, to meet a case-based fiduciary standard of admissibility.

Parties may still revise or reject proposals according to their own lights, but the language of the proposal, and the focus of the process, are altered to facilitate adversarial argument in the production of joint problem solving.

KEYWORDS
Online Dispute Resolution, Alternative Dispute Resolution, Joint Problem Solving, Object of Value, Argumentation, Negotiation, Qualitative Decision Theory, Practical Reasoning, Risk Analysis, Planning, Fair Division

1 INTRODUCTION

1.1 ODR

In harmony with wider changes in society - in particular the advances in technology and the large scale use of online services to transact all forms of business - recent developments in the field of online dispute resolution (ODR) have led to a new and deep interest in their use as one of the best alternatives to the trial in several law domains, like consumers and family disputes (originally, ADR, alternative dispute resolution).

ODR will help reduce obstacles to the good functioning of civil proceedings, negotiations and settlements, especially the cross-border ones, by enforcing a method that could improve agreements using processes that use argument to reach joint settlement. These areas include successions and trust and matrimonial regimes in a first stage, and later in other areas such as property and lease, company law and consumer law.

SquareTrade and other websites like Internet Neutral, WebMediate, and even Wikipedia have rule-governed processes and web-based forms to facilitate the resolution of disputes. AI and Law has published many contributions to e-Negotiation, from logics to systems, for over two decades.

It is the creation of e-procedure that triggers the engagement of a number of important legal and non-legal approaches. The first is the use of reason – let me persuade you that this is the way to settle (what Roger Fisher called “principled negotiation”). Many researchers have worked over three decades to deliver models of argument based on rules and precedents, and have applied these formalizable forms of argument to negotiation and appraisal of the relative desirability of outcomes.

However, to reach a solid agreement, engaged people need more than merely rational-economical forces. E-procedures based on game theory principles of fair division and win-win solutions can be more satisfactory than using law principles, but AI ideas and representations can bring even more, much needed nuance.

1.2 Focus on Procedural Fairness

Fairness has usually been conceived either in terms of fair outcome distribution (distributive justice), or fair procedure (procedural fairness). For example, Last-Diminisher, Divider-Chooser, Taking-Turns, Selfridge-Conway, Moving-Knife, Lone-Chooser, and Adjusted-Winner can all be considered procedural
1.3 Focus on Describing Outcomes

One promising thread of AI research on automated negotiation gives more attention to the outcome description, what is called the “object of value” in economics, rather than the mere process of agreeing and arguing.

Loui and Moore, in “Dialogue and Deliberation,” suggested that game theory’s bimatrix of utilities, where traditionally a single number for each “player” represented the value of an agreement, might be replaced with something more dynamic.

In the simplest example, a utility value would be replaced with a set of parameters for an optimization or search problem. The parameters would be fixed by agreement, such as the requirements in a Traveling Salesman Problem, but the agent’s utility would be based on how much, how well, and how fruitfully the agent performed subsequent search. In this model, one may have appraisal estimates, but not final values, for settlements. An agent must search the space of what can be done with the settlement even as the negotiating agents search for a settlement.

That paper also discussed a more widely applicable representation. Many negotiation outcomes would replace the numeric utility value with a fragment of an AI plan, where action, contingent action, logical derivation of successor states (perhaps uncertain), and logical derivation of properties at states that might have value, all add complexity.

In many ways, the partial plan, or plan fragment, as an outcome of negotiation is a compromise between a legal contract and a decision tree or search tree, as one might expect.

A game theoretical model on its own is sometimes not enough for the ODR participants’ needs. However, coupled with an AI model which could integrate features such as dialogue and possibility of reformulating there could be chances for ODR’s rise.

1.4 New Objects of Value

In this paper, we propose an improved representation for the object of ODR. It is based on a new idea for the objects of value that specifically brings familiar risk analysis and decision theory ideas into the orbit of argumentation. It was originally intended to solve two problems in decision theory that result from too much simplicity in outcome representation.

The problem of externalities, or “borrowing from the environment,” appears in decision models primarily because the dimensions of value are fixed. Like PCA in machine learning, there are some dimensions that command the highest priority, such as dollar-cost and square-foot return. If they are easily quantified, they enter the decision model as part of a multi-attribute utility. Inevitably, the result is an economics geared toward the accounting of quantities, usually artificial and socially constructed measures. Hard choices tend to be solved by avoiding some tradeoffs, with hidden costs in the dimensions that are hard to quantify, thus escaping the model: environmental impact, due diligence, fiduciary responsibility, ethical standard, quality of relationships.

This is a well known problem when one person is “arguing preferences” in one’s own head. The same issues arise when two people are seeking joint settlement. The solution is to permit dynamic introduction of new dimensions, even when value is not easily quantified. The precision of utility models may have been a mirage even over quantifiable factors. Moving from maximization and discounting to argumentation releases the Bayesian bonds.
The problem of short horizons, or “borrowing from the future,” appears in decision models primarily because it is hard to put value on streams of events. It is easier to define outcome states, to fix the horizon, assess utility synchronically, and ignore all pain and joy that precedes or follows. Utility theorists understood this from the start and took lotteries to be over objects as complex as the model needed to be. After the roulette wheel, the tax should be added.

This is nice in theory, but in practice, it is difficult to model past and future and bring utility to their appraisal. Moreover, as scenarios move further into the future, causality of action, enumeration of events, precision about probabilities, all turn from good guesses into pure fiction. Hence, decision models tend to have modest future envisionment. For dispute resolution, the same happens. Even if the language of an offer or settlement is precise with respect to important future events, the ability to put a utility value on the implied scenarios is beyond most reasonable people.

A different ontology for outcomes is needed: a structure that is fairly compact, but expandable; that succumbs to arguments over fairness or inadequacy, not just mathematical discount by probability; that admits imprecise but important valuable considerations; and that looks at a trajectory, not just a snapshot in time.

A new idea starts with a path of milestones that would be subject to pro-con argument, for the single agent. Here, the idea is extended naturally to pro-con argument among parties to a negotiation.

2 MATHEMATICAL REPRESENTATION

A proposal is a set of commitments, some conditional, others compulsory, and a set of milestones \((m_1, \ldots, m_n)\) that define a trajectory.

It is important to note that \(n\) is not fixed: in a single negotiation, some proposals may have one length and time step, while other proposals may refer to milestones at completely different times.

In the degenerate case, a trajectory is an end state and \(n=1\), which is typical in game theory, decision theory, and much research on negotiation.

A set of transition probabilities link the milestones, \(p_i\), but the trajectory is a path, not a tree, so this is not a Markov model or other stochastic state-transition model. In the terminology of Herbert Simon, it might be an “aspiration,” or what AI might now call a planned path.

The probabilities are mainly used here to claim that each milestone is sufficient to make the next milestone probable (we will soon permit parties to argue over what is sufficient probability). In classic AI planning, deduction would require a probability of 1 for all transition probabilities. In decision theory, the probabilities would be less than 1, but each milestone would have multiple successors. This is of course too hard to model in practice beyond simple, encapsulated situations. In risk analysis, the probabilities are improved by adding commitments, usually best-effort mitigations, in the face of hazards. For negotiation, joint commitments will improve probabilities. “We both want the successor milestone, and I am willing to commit to a, so if you commit to b, the probability will be acceptably high.”

A set of identified events, \(E_v\), with investment and response policy commitments from each participant, Inv and Resp, permits probability arguments for each transition probability. Probability arguments can be based on conditionalization, reference class considerations, or even judicial reasoning to a standard of proof, evidence or care. They need not be numerical probabilities because they will not be multipliers of utilities here. If one has the precision to do an expected utility calculation that can be accepted by all parties, that can be part of the description of a milestone, not its final valuation. Here, qualitative probabilities, from numerical ranges to values such as “more likely than not” can enter the model.

Attributes (or aspects, attainments) that have value can be attached as part of the description of the milestone, \(a(m) = (a_1, a_2, \ldots, a_k)\). These are collected as \(v(m) = (v_1, v_2, \ldots, v_k)\). Not all milestones will have the same attributes, nor even the same number of attributes that describe them. As the milestone extends further into the future, one would expect the attributes to be fewer. But some chance-qualification may simply change “has car” to “probably still has car”. Here, qualitative objects of value, externalities, and ineffables can enter the model.

If one would like to theorize about multiple branches in a lottery, as one would in classical decision-theoretic representation of the future, one could set one attribute to be, e.g., 0.3-probability-of-payoff, and another attribute to be, e.g., 0.7-probability-of-loss.

Attitude toward risk would then enter the multi-attribute appraisal, to the extent that two values can be reduce to one. For some, 0.3-chance-at-positive-$100 and 0.7-chance-at-negative-$100 has the same value as $0; for some, it has the same value as negative-$40. Note that the case-based reasoning, or other argument-formation mechanism, is doing all of the work that microeconomics finds traditionally interesting. Rather than model risk precisely, it may be that an ADR process or ODR system simply judges certain lotteries to be “in bounds” and admissible in the sense of “fair, not foul,” and leaves further appraisal to the disputing parties. It may not be the job of the case-based projection to determine optimality, or right and
wrong proposal, but simply that the proposal is not unfair on its face, by the standards of the arbiter.

We do not suppose that all k attributes carrying value can be so reduced. Chances mentioned in milestone descriptions are different from transition probabilities that provide guarantees of the connectedness of the trajectory. Remember that \( p_{ij} \) might often be simply “meets the standard required by this court.”

Arguments for and against a trajectory take several forms:

(1) proposing a trajectory;

(2) deriving parts of a description of a milestone;

(3) adding to the considerations that describe a milestone;

(4) adding to the hazards that might strengthen or weaken a transition probability;

(5) giving a probability argument for a transition probability based on statistics, precedent, or statute;

(6) arguing that the trajectory, taken as a whole, meets a fiduciary standard, a fair division, or an improvement over BATNA (best alternative to a negotiated agreement).

Arguments of types 1-3 are familiar to dynamic planning in AI (though unfamiliar to decision and game theory).

Arguments of type 4 are inherited directly from risk analysis in reliability and safety engineering, as well as policy planning in management.

Arguments of type 5 are familiar to certain kinds of non-Bayesians who construct probabilities directly from data, and even to some Bayesians and objectivist probabilists who can conceive of conflicting evidence. Type 5 arguments to a standard of proof, and type 6 arguments, are familiar to those who study case-based reasoning.

Type 6 arguments could also yield to machine learning, especially for ADR/ODR. This is because typical settlement is just as meaningful in ADR as justified settlement. Machine learning projections can also carry normative force when the training examples are exemplary and the features are connected to principles.

Another way that type 6 arguments can be made is through the construction of preference, or utility arguments.

The logical notation of the arguments is beyond the scope of this paper, and has been discussed thoroughly throughout the past decades of AI and Law.

3  EXAMPLES

3.1 One-Shot Tug of War

Before showing where this representation can be helpful, it is instructive to show where it is equivalent to classic outcomes.

Two parties are negotiating a price in a bazaar. The seller asks for 100€, while the buyer proposes 50€. There is one milestone, \( m_1 \), with one attribute, price-paid\( (m_1) \). Perhaps a new proposal makes a compromise on price:

\[
a_1(m_1) = 75€
\]

Values are easily compared to reference objects or alternate scenarios. There are no transition probabilities, and \( k \) is fixed. So there is not much to argue about except the fairness of the proposal. Arg( Fair-Settlement\( (m_1) \) ) might be based on Arg( Typical-Settlement(price-paid\( (m_1) \) ) which might be based on prior cases, statistically or prototypically, with the usual defeasibility and specificity of generally similar, relevant, on-point prior cases.

3.2 One-Shot Exchange to Two Shot

An even better way to represent the same situation for the purposes of ODR would be to name the objects in the exchange:

\[
a_1(m_1) = \text{semi-antique-Tabriz-3x5-area-rug}
\]

\[
a_2(m_1) = 100€
\]

because by doing so, it becomes easier to create variations of the proposal:

\[
a_1(m_1) = \text{semi-antique-Tabriz-3x5-area-rug}
\]

\[
a_2(m_1) = 50€-and-promissory-note
\]

followed by a second milestone:

\[
a_1(m_2) = \text{semi-antique-Tabriz-3x5-area-rug}
\]

\[
a_2(m_2) = 50€-prior
\]

\[
a_2(m_2) = 50€-at-this-later-time
\]

where there remains room to put a specific calendar timing on the second payment (and possible documentation of fulfilment of the promissory note).

3.3 Two-D Exchange to Three-D

Another variation of the last exchange introduces a side consideration while remaining one-shot:

\[
a_1(m_1) = \text{semi-antique-Tabriz-3x5-area-rug}
\]
Now the question remains how each party will value the third attribute of the exchange, and how one might argue the fairness of the exchange, the typicality, or the acceptability.

Note that $p_{12}$ must be assessed, which is not remarkable here because the prospect of making good on a promise to make a second payment is guaranteed by the good regulation of commercial contracts. One might still argue that this probability does not meet the required standard of trust when transacting in a bazaar. And one might raise the possibility of hazards: what if the buyer cannot find the way back to this seller’s stall, even with good faith effort?

### 3.4 Expected Utility Example

Utility theory is built on the idea of a lottery, so let us suppose that the later payment is the result of a coin flip. Such deliberate introduction of lotteries is a popular, if somewhat unprincipled way of reaching agreement.

\[ a_3(m_1) = \text{fair-coin-lottery-on-Apple-watch-series1-slightly-used} \]

This same proposal might be reformulated as:

\[ a_3(m_1) = .5\text{-chance-at-Apple-watch-series1-slightly-used} \]
\[ a_4(m_1) = .5\text{-chance-at-no-Apple-watch} \]

and it may be that $(v_1, v_2, v_3, v_4)$ is arguably acceptable to both parties to the deal.

Note that acceptability is not entirely dependent on arguability. As in any negotiation, each party has the ability to hold out, against reason and persuasion. This notation simply captures the structure of contracts under deliberation, so that the world is not seen entirely as lotteries, with no future consequence, and no widening of concerns. Actual ODR systems show us that the more aspects that can be put into a template, or supported with a formal ontology, the more support that can be given by AI, prior examples, and other analytics. Without added structure that is likely to be used by disputants, ODR reduces to a free-text, message-and-response system.

### 3.5 Future Entailment Example

The real power of this flexible “scoring card” starts when it produces the ability to object to an offer because of downstream ramifications.

Labor might propose that employees be allowed to take 8 weeks of vacation each year, for the next five years in exchange for electronic workplace monitoring privileges, a straightforward exchange.

\[ a_1(m_1) = 8\text{wk/yr vacation} \]
\[ a_2(m_1) = \text{labor-acquiesces-to-surveillance} \]

But one might argue that a sufficiently probable entailment of the new vacation policy is reduced productivity, hence, reduced profitability.

\[ a_3(m_2) = \text{worker-output-down-10-20%-over-5-ys} \]
\[ a_4(m_2) = \text{company-profits-down-10-20%-over-5-ys} \]

and that these two new attributes have non-trivial effect of desirability or even acceptability from a disinterested observer.

Of course $p_{12}$ can be counterargued. It might be that with greater vacation time, productivity and profitability soar, based on similar companies in the same industry situated similarly. Or it might be that surveillance leads to decreased productivity. $m_1$’s probabilistic causal influence on $m_2$ is an important part of the proposal.

A reasonable hazard might be decreased demand over the five year period. One side might commit to the conditional response policy of accepting furloughs. This has the effect of maintaining the probability that the productivity and profitability decline will not go higher. Argument is free to mention hazards, though an effective ODR procedure might place a limit (like the number of appeals or objections), so parties have to prioritize their concerns.

### 3.6 Additional Aspect Externality Example

As promised, the “negotiation scorecard” also permits the introduction of additional concerns, so these templates, taken as contractual agreements, do not reach agreement at the expense of hard-to-quantify aspects. In this example, the same maneuver happens as in 3.3, but for different reasons (mitigation requirement, not win-win logrolling), and with more long-term importance. Externalities are too important to leave external to the modeling, even if their value is hard to quantify.

\[ a_5(m_1) = \text{increase-energy-output-at-least-10\%} \]
\(a_1(m) = \text{increase-cost-less-than-10\%}\)

This might be a fair deal to strike, as seen by both parties. But one party, or even a third-party arbiter, might introduce

\(a_3(m) = \text{emissions-output-gain-30\%-after-3-yrs}\)

There may be models in risk analysis that permit flexible accounting of aspects, without insisting on quantifying the value associated with those aspects. Risk analysis also tends to have an implicit dialectical, adversarial or multi-party procedure and event/investment/response calculus.

But risk analysis tends to get stuck evaluating the probability of hazards (usually too small to quantify) and their distorting disutility impacts (usually too large to measure). The major departure here is the retreat from optimality to admissibility of paths. Then probability is used to hold together the steps in the paths. In dispute resolution situations, the path is a joint envisionment of the future, and the investments and committed responses are joint problem solving.

### 3.6 Child Custody Example

A most important application of ODR is negotiation of child custody in family court. The tug-of-war typically occurs in the time-spent-with-child or present-at-holidays dimension, though support payment levels may also be subject to barter.

\(a_1(m_{10}) = \text{roughly-equal-visitation-by-day}\)

\(a_2(m_{10}) = \text{roughly-equal-presence-at-holidays}\)

The question might be how to achieve, ten years later, a rough equivalence of divided time (one might even be specific, such as no-more-than-10\%-inequality).

Regardless of how the path sets out, there are clear hazards. A small event, such as a non-electively missed holiday, may be corrected with joint commitment to a response policy of trading the next holiday. This is a non-specific hazard, so there is a question of whether the analysis permits hypothetical events with responses that generalize from the specific to non-specific. One way to do the analysis is to create a milestone for the end of each year and give a specific anchored-by-year response commitment for each anchored-by-year hazard.

\(a_3(m_{10}) = \text{reasonable-cumulative-stress-on-child}\)

What the dialectic permits us to do here is to respond to a specific argument, in this case a specific, hypothetical, calendar- or transition-anchored hazard, with a specific response commitment. An efficiency is achieved because the rebuttal need only respond to the counter, not to all similar counters at any other time.

Thus, the ODR process uses argument to achieve the bones of an agreement, not to flesh out the full body or text of the final agreement.

A much larger hazard is also hypothetical:

- **Event** = parent-job-is-transferred-out-of-state;

Then the transition probabilities may remain sufficiently high for reaching \(m_{10}\) as a path from \((m_1, m_2, ..., m_{10})\).

But a reasonable rebuttal, again, possibly from the ODR AI or third-party arbiter, is the stress on the child,

\(a_3(m_{10}) = \text{reasonable-cumulative-stress-on-child}\)

which may force a reduction of aspiration from no-more-than-10\%-inequality, to perhaps no-more-than-25\%-inequality.

In an ODR setting, many of the concerns and aspects will be known to the system, available in menus (or shared across cases, like prior search phrases), with prior case opinions on fairness. This is the AI analogue of actual family court settlement design space, where custody agreements are struck as variations on one another routinely.

### 3.7 Actual ODR Cases

Giacalone’s recent dissertation on ODR looked at 300 cases of child custody. In his opinion, over 200 would have benefitted from the more complex representation described here, primarily because of the assignment of non-comparable items in family disputes. Cases turned on such things as

- a) the approval of a separation agreement in time
- b) the termination of a joint tenancy
- c) the judicial separation
- d) the division of multiple assets held as property
- e) the judicial separation and restitution of defined goods
- f) the division of defined goods and adequate compensation for indivisibles
g) the switch from a judicial separation to the approval of the separation agreement

h) the custody of a child

Neither King Solomon, nor the family court, can entertain fair-division divider-chooser strategies for all of these aspects.

4 Discussion

4.1 Fiduciary Standards

Negotiation in the AI planning and discourse community is seen as joint problem solving. There, the problem solving is the same as the dialectic over events and commitments. We add another theme, which is the idea of co-piloting or team-shepherding a trajectory through a dynamic, even treacherous time-and-value terrain.

Far from the idea of a zero-sum game, where each side aspires to deny, in order to acquire, we choose a representation that asks participants to agree on aspiration, then bargain over how to make it possible.

The thinking is that each side should be bound as a fiduciary to the attainment of the milestones. Fair division is not so much about splitting the pie as it is about allocating and shouldering responsibilities, e.g., to guarantee that the pie is not left out in the rain. Especially since arguments from precedent are likely to reflect judicial opinion on standard of due care, parental, labor, or owner rights and responsibilities, rather than past frequencies, perhaps fiduciary standards are a good metaphor. Optimality certainly is not an appropriate metaphor.

4.2 Traditional Negotiation Ideas

One might ask what has happened to some traditional ideas that occur in game-theoretic conceptions of negotiation.

Where is equilibrium? There is a judicial background to the agreements, so self-enforcement is unnecessary.

Where is power resulting from having a good security (BATNA) position or a believable threat to walk away? Being well positioned to make a deal, or make a threat, is still present. That happens in the minds of the participants and is not modeled formally here. Our focus is on the object of the proposed agreements, and their appraisal on objective (third-party observer, rational persuasion, or principled negotiation) grounds. We have exchanged utility values in a game matrix for admissibility arguments over strands of partly specified paths into the future.

Even when a 1000-page contract is written, as a particular proposed agreement, that proposal sits within a zone of potential agreements, a process of choosing which proposals to make, each party’s evaluation of the proposal relative to other perceived options, and so forth.

We have moved away from the concepts of ask, bid, and concession, i.e., price haggling, toward a kind of problem solving that leads specifically to joint protection and control of the envisioned, aspirational path.

As with most joint problem solving dialogues, the pro-con process may be considered just “cheap talk” by economists, which perhaps shows how differently economists have approached negotiation. Focusing on a specific kind of dialogue, to produce arguments over shared fiduciary responsibility, reduces the risk of emotional distress often arising from less focused cheap talk.

4.3 Returning Attention to ODR Systems

Other ODR systems proposed in the literature can support logrolling as this representation does. There is probably little precedent for case-based scrutiny of a path. AI negotiation generally considers channeling discourse toward productive joint problem solving. This representation puts much more burden on the use of probability arguments, and joint problem solving associated therewith.

Instead of asking “HOW MUCH?” or “WHAT IF I WALK AWAY?” our system will tend to ask “WHAT ELSE MATTERS TO YOU?” “WHAT DO WE WANT TO HAPPEN NEXT?” “HOW CAN WE MAKE THAT HAPPEN?” “WHAT CAN JEOPARDIZE THAT FROM HAPPENING?” “WHAT STRONGER GUARANTEE CAN BE MADE WITH A CONDITIONAL COMMITMENT OR UNCONDITIONAL INVESTMENT?” Those are the variations on a proposal most easily represented here.

Instead of saying “THIS BUNDLE IS WORTH $x” or “THIS LOTTERY IS WORTH $y”, the system will naturally ask “HOW CAN THIS MIX OF ATTRIBUTES BE IMPROVED?” perhaps “AT THIS TIME” or “AT A LATER TIME”. The argumentation is focused on the question of “IS THIS MIX OF ATTRIBUTES ADMISSIBLE?” i.e., to a third-party arbiter, or given precedent similar settlement. It places the focus on arguing that “THESE COMMITMENTS MEET THE REQUIRED FIDUCIARY STANDARD FOR TRAJECTORY LIKELIHOOD” rather than “YOUR PROPOSAL IS UNACCEPTABLE”.

The artificial intelligence picture of the agent will be preferred to the game theoretic one in the modelling of interactions in direct proportion to the extent to which knowledge informs creativity. The main difference is that AI’s models consider topics such as
planning, knowledge representation, automated reasoning and argumentation as a separate field of study. Can any of these pieces help facilitate, even automate, creativity in negotiation?

The drawback of game theory’s models starts with the fact that – compared to AI’s models – they seek to explain settlements in a static problem formulation with static valuations of proposals. The key point is that negotiation includes more important phenomena such as dialogue, planning, focusing and reformulating. The aim of an AI model deployed in ODR is of fitting all the pieces together, with a better design space for proposals.

We cannot of course merely support participants making natural language text proposals in text boxes as ODR. So in this paper, we borrow a more flexible representation of objects of value, from an effort to put decision and risk analysis in better alignment, and find that (perhaps not surprisingly) the components also fit the semi-adversarial, semi-cooperative situation of negotiation.

Many disputes have multiple components and without sophisticated tools to deal with the inherent complexity, decision-makers are forced to deal with issues one at a time. A piecemeal approach to negotiation encourages positional rather than mutual gains bargaining. Various issues and outcomes may lead negotiators to make decisions based on psychological dynamics and emotion rather than reason.

Moreover, reasonable outcomes are compromised when decision-makers make logic errors, take shortcuts, or permit emotions to get the upper hand when under the stress of intensive negotiations. Without properly assessing the risks, parties are often unrealistically confident of a favourable outcome, should the matter be taken to court.

Leaving the old idea of utility as an archaic measure of the intensity of preference, and admitting ideas from AI, generally, and AI and Law, specifically, brings new opportunity. A whole category of disputes currently not being considered for ODR may become appropriate for application of comprehensive e-negotiation systems, such as family disputes, with more attention paid to controlling trajectories instead of fighting over portions.

5 References


Carneiro, Davide, Paulo Novais, Francisco Andrade, John Zeleznikow, and José Neves. “Using Case-Based Reasoning and Principled Negotiation to provide decision support for dispute resolution.” Knowledge and Info. Systs. 36.3 (2013): 789-826.


Game Theory:
if player a does a3, player b can do b4

Bargaining Theory:
a's and b's proposals are close

Planning Theory:
do more search? do more analysis of the outcome?

Negotiation in AI:
evaluation of proposals depends on plans, which can be deepened