Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Constrained Rationality: Formal Goals-Reasoning Approach to Strategic Decision & Conflict Analysis

Majed Al-Shawa
Electrical & Computer Engineering
University of Waterloo
Waterloo, Canada
mmalshawa@uwaterloo.ca

Otman Basir
Electrical & Computer Engineering
University of Waterloo
Waterloo, Canada
obasir@uwaterloo.ca

***Abstract*—This paper proposes Constrained Rationality, a formal qualitative goals and constraints reasoning framework for single and multi agents to analyze and rationalize about strategic decisions/conflicts. The framework suggests bringing back the strategic decision making problem to its roots: reasoning about options/alternatives, not to satisfy a set of preferences, but rather to satisfy the explicitly stated strategic and conflicting goals an agent has, given the internal and external complex and conflicting realities/constraints the agent has. The paper analyzes the relations among goals and constraints, how value property labels for goals (such as their achievement or prevention levels) propagates through these relations, and proposes a set of propagation rules and an algorithm to calculate the final value labels for goals at any point of time. The paper also presents some preliminary experimental results on using the algorithm to reason about a business strategic decision making scenario.**

***Index Terms*—Strategic Decision Analysis, Conflict Analysis, Decision Support, Formal Reasoning Methods, Agents Reasoning, Multi-Agent Systems**

I. INTRODUCTION

Strategic Goals, organizations or even individuals have, are different than operational or tactical goals. While operational and tactical goals are clear and concise with limited scope and short-term implications, allowing them to be easily formalized and reason about, strategic goals tend to be more general, less clear, complex, with broader scope and long-term implications.

Strategic Decisions to address the strategic goals are enterprise wide decisions that deals with the survival and prosperity of the origination, its directions, its partners, markets it wants to be in, lobbying it must do, etc. Conflicting goals, conflicting realities, internal constraints, outside regulations, and so on, are the norm for enterprise strategists. At the same time, departments and lower rank managers consider limited scope decisions where the environment is mostly well defined and under their control. Strategic goals for individual agents, such as balancing life and career goals, seem difficult to deal with, while mobilizing a tactical goal, such as “what movie to watch tonight”, is an easy one. At the tactical level, options can be identified clearly, preferences can be elicited with no vagueness, and strict assumptions could be applied. But at the strategic decisions level, options are not complete/clear and preferences are harder to establish. While decision theory, game theory and related-ones can be used effectively at the tactical decision making situations (ignoring the many criticism and reported failures or lack of use/intrest in practice), there is a need for a formal reasoning framework to address the challenges of dealing with strategic goals and decisions.

Because of the many limitation of the decision theory and game theory approaches for MAS (as discussed in [1], [2]), a new direction starts to emerge within the research community, namely within the AI multi-agent BDI and software requirements engineering comminities: Modeling Goals and Reasoning about them (e.g. [3]–[10]). But the current frameworks lack the representation mechanisms to support modeling goals, and therefore reason about them. Recently, in [10], we talked about the short comings of the current frameworks, and the need to extend them at different levels to be able to make them well suited for multi-agent knowledge-based systems; and proposed a new conceptual knowledge modeling and management framework to address these short comings especially with regards to strategic knowledge management and decision making in MAS.

In this paper, we extend our previous work, and propose to bring back the decision and conflicts analysis to its roots: reasoning about goals and plans to achieve the strategic goals the agent has. We propose a formal qualitative goal-reasoning framework, named here: Constrained Rationality. The framework will allow decision makers, especially at the strategic level, model their goals, model their internal and external constraints (realities which limit or open opportunities to their goals - from this the name of the framework came), model the interrelations among these goals and constraints and how they affect each other, and then finally evaluate their plans based on the collective overall goals-constraints model they have.

We, first, in Figure 1 show a business strategy decision making scenario in which a leading Car Manufacturing company (CM) modeled its strategic goals to survive the hardships it is facing in the economical crises of today, and to achieve prosperity in the future. The company used the Constrained Rationality framework to prepare a complex model of its goals and constraints (shown in the figure) with goals affecting/conflicting with each other. Using the reasoning framework, CM wants to test two plans, to see which one satisfy its immediate short-term survival needs while keeping in mind the long-term prosperity goals: 1) plan to accept a bailout from the government; and 2) declare bankruptcy.

978-1-4244-2794-9/09/$25.00

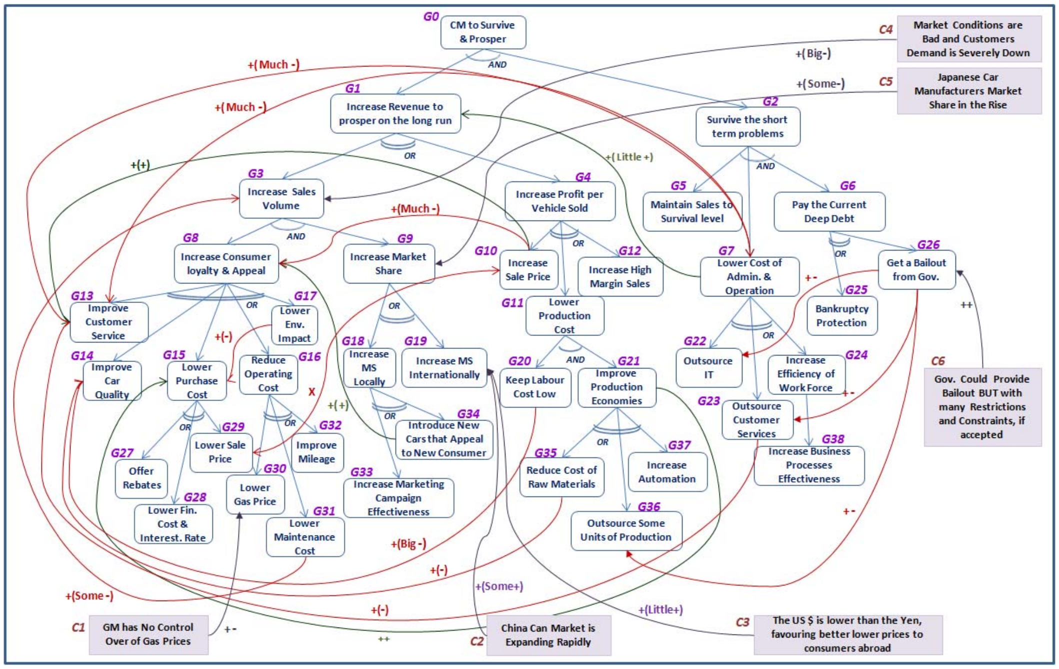

Fig. 1. Example of a possible Goals & Constraints Model (GCM) for a Car Manufacturing (CM) Company

Later in the paper, we will use this example as a preliminary experiment and report on its results. In section 2, we introduce the Goal and Constraints Model (GCM) and its constructs. Section 3 will discuss the concept of qualitative labeling of goals' value properties, such as the goals' achievement, operationalization and prevention. Section 4 and 5 will discuss how the goals' value labels get propagated across the relations exist among goals and constraints. In Section 6, we put all the pieces together and introduce a formal forward qualitative value propagation algorithm to analyse plans/options based on expressed initial set of value properties of the agent's goals and constraints. Finally, we conclude in Section 7 with remarks on our preliminary experiment, limitations, and future work.

II. AGENT'S GOALS& CONSTRAINTS MODEL

In [10], we proposed the Viewpoints-based Value-Driven Enterprise Knowledge Management (ViVD-EKM) framework, a conceptual modeling framework to model Multi-Agent Systems. As per ViVD-EKM, the agent will have Viewpoint models about the world he perceives. These Viewpoints models are structured in a way that each could represent the agent's own knowledge about a topic, a situation, or a specific agent/player in his world. At the heart of each Viewpoint model is the *Goals & Constraints Model* (GCM), a sub-model of the agent's Viewpoint model. GCM captures the agent's goals and constraints with regard to the specific situation/conflict his viewpoint model is concerned with. The goals within GCM is operationalized by a set of plans (or processes).The detailed ontology of GCM, Viewpoint, and the full ViVD-EKM conceptual modeling framework is given in [10]. Figure 2 shows an illustration of a simple one goal-tree GCM model.

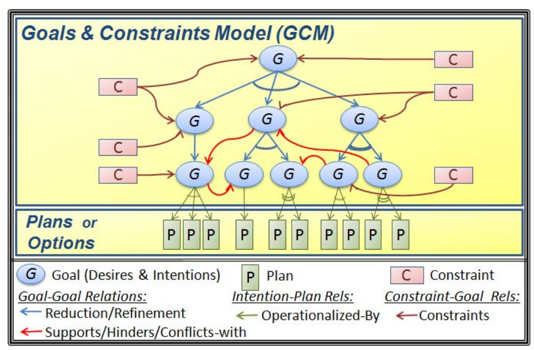

Fig. 2. Goals & Constraints Model (GCM), with simple one goal-tree

The goal nodes in GCM represent the motivation the agent has. Goal nodes are modeled by first inserting the ultimate strategic goals the agent has. Then go through a reduction process, by using reduction relations, refining these big goals, called *Desires* in ViVD-EKM, to a set of smaller Desires, and so on until a set of primitive very-refined goals, called *Intentions* in ViVD-EKM, are produced. Intentions are goals that could be operationalized by means of Plans, whilst Desires are goals that could be operationalized by other Desires or Intentions. The end result of the goals reduction process is a goal tree, or a set of goal trees, where ultimate strategic Desires form the roots of these trees, and with Intentions at the bottom of each goal tree.

Goals could have among them a different type of relations:

Goal-to-Goal (G-G) Lateral Relations, to differentiate them for the top-down reduction relations . These relations represent the supporting, hindering or conflicting effect which some goals could have on other goals. For example, in CM's GCM shown in Figure 1, the achievement of "Outsourcing Customer Services" goal (G_{23}) will have a negative impact (hinders or prevents to some degree) the achievement of "Improve Customer Services" goal (G_{13}). We will discuss later the different types/effects of G-G Lateral Relations.

An important component of the GCM model, is the set of *Constraint* nodes it has. In this paper, we treat all constraints similarly as Constraint nodes without differentiating between internal and external (to the agent). An important fact about constraints is that they represent not only limitations on goals, i.e. affecting goals negatively, but also they could represent opportunities. For example, In the CM example, the "Government Bailing out Auto Industry" constraint (C_6) will provide a positive opportunity for CM to achieve its "Get a bailout/help from the Gov." goal (G_{26}). Note that the constraint will not guarantee achievement to the goal, it only provide opportunity to the goal to be achieved to an extent set by the constraint. The actual achievement of CM's G_{26} goal will happen through some plan that CM will commit itself to, a plan which most-likely have a negative impact on other goals CM has, such as the Outsourcing goal indicated earlier (because the government will not allow outsourcing as part of the bailout conditions). Constraint nodes are connected to the goal nodes through Constraint-to-Goal (C-G) Lateral Relations, a set of relations similar to the G-G Lateral relation but slightly different. We will discuss them later in the paper.

Each modeling construct/concept, with the ViVD-EKM conceptual framework, has multiple *Values* (*Value Properties*). For the purpose of introducing a formal reasoning framework, we will use only three important Value Properties attached to each goal, and two Value Properties for each constraint. First, *Goal Achievement* is a value property that provides a measure of the achievement level of the goal. Goals' achievement levels propagates up the goals reduction tree from the intentions at the bottom (based on results from the plans attached to those intentions) and up the goals tree until a value is assigned to the achievement level of the goal, or through the G-G lateral relations. Constraints also have *Constraint Achievement* value attached to them to reflect the true reality/strength of the constraint as imposed by the enforcer, or as believed to be enforced/exist. Second, *Goal Prevention* is a property that describes the hindering (negative) effect that a goal's achievement has on another goal. For example, if an agent has a goal to "increase Sale Price for Product *A* and another goal to "increase Sales Numbers for *A* by 50% this year", then we know for sure, from experience, that increasing the sale price of *A* will impact negatively the goal to increase *A* sales preventing it from happening at least in the short term. The question is by how much? The Goal Prevention value's aim is to capture the answer to this question. The Prevention property is especially important to track conflicing/hindering effect that may be hidden otherwise (if we have only achievement level indicators for goals). Constraints also have *Constraint Prevention* values attached to them, to reflect the prevention the constraints suffers from, stopping them fully or partially from having their effect on the goals they are attached to. Finally, *Goal Operationalization* is a value property that describes the operationalization level of the goal node. This property will state whether the agent has committed itself to a set of plans that will ensure a degree of operationalization for the goal, or not. Higher goals in the trees have operationalization levels that reflect the degree of operationalization that is provided to each by the lower level goals, mainly the Intentions. It is important to track Operationalization, separate from Achievement, because the maximum level of achievability possible for any goal depends on the level of operationalization the agent commits to it. Only goals could have Operationalization values.

In the following section, we will discuss the process of fuzzy labeling of these value properties, then we will discuss how the value labels of these value properties get propagated through the relations connecting goals and constraints to goals.

III. Fuzzy Labeling of Goals and Constraints Value Properties Relations

As a matter of notation, the *GCM* mode is a graph like structure $\langle \mathcal{G}, \mathcal{C}, \mathcal{R} \rangle$ where $\mathcal{G}$ is a set of goals, $\mathcal{C}$ is a set of constraints, and $\mathcal{R}$ is a set of relations over $\mathcal{G}$ and $\mathcal{C}$. Let the value properties of Operationalization, Achievement and Prevention for each goal $G_i \in \mathcal{G}$ be represented as variables $Opr(G_i)$, $Achv(G_i)$, and $Prvn(G_i)$ respectively; and the Achievement and Prevention value properties for each constraint $C_j \in \mathcal{C}$ be represented as variables $Achv(C_j)$, and $Prvn(C_j)$ respectively. In addition, let the set of variables, for each goal and constraint, track the different level-of-satisfaction for the value property it represent for the goal/constraint. In general, the level of satisfaction for each value property could be expressed numerically as a percentage number between 0 to 100%.

For the purpose of the Constraint Rationality's qualitative reasoning framework, let us consider a limited number of satisfaction levels (instead of considering all the levels between 0-100%) for these value properties' variables. And let these limited set of levels be defined as fuzzy sets, each is given a name which represent a meaningful linguistic label such as Full, Partial, Little, Some, Big, etc. Each of these fuzzy sets to be defined by a fuzzy membership function mapping the actual satisfaction level of the property (within the fuzzy domain of the property satisfaction level: 0-100%) to a set membership degree $[0, 1]$. While the fuzzy domain of any value property's satisfaction-levels can be divided into any number of fuzzy sets, as deemed sufficient and beneficial to the framework user, caution should be exercised to maintain usability (this is not a restriction). For this paper, we introduce a simple but sufficient scheme to divide the fuzzy satisfaction level domain of each value property to seven sets: *Full*, *Big*, *Much*, *Moderate*, *Some*, *Little*, and *None*. These fuzzy sets will covers all the value properties (Operationalization, Achievement or Prevention) for goals/constraints, as shown in Figure 3. The figure shows the memberships functions for each set to be trapezoidal in shape, for simplicity only (not as a restriction). In practice, the number of fuzzy sets and their membership functions should be defined based on the user needs and requirements.

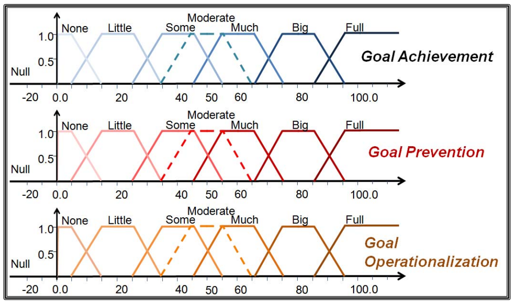

Fig. 3. Fuzzy Sets dividing the satisfaction levels domain of the different Goals' Value Properties (operationalization, achievement, and prevention)

Now, let us introduce $\mathcal{L}$ as a set of labels. The elements of $\mathcal{L}$ matches in number and names the fuzzy sets chosen to divide the satisfaction levels domain of the operationalization, achievement, and prevention value properties. In our case, $\mathcal{L} = \{\mathit{Full}, \mathit{Big}, \mathit{Much}, \mathit{Moderate}, \mathit{Some}, \mathit{Little}, \mathit{None}\}$. And let $Full > Big > Much > Moderate > Some > Little > None$, matching the order of the fuzzy sets coverage over the satisfaction levels domain, with the meaning that the *Full* label represents a higher satisfaction level than *Big*, and so on.

Let the *Achievement* value property of a goal G_i is represented as $Achv(G_i) \geq L_{achv}$, where $L_{achv} \in \mathcal{L}$, and L_{achv} is a label that matches the name of the fuzzy set which the achievement level of G_i has the highest membership of. For example: if x_i represent the achievement level of the goal G_i and $x_i = 94$, and the achievement level of G_i has memberships of $\mu_{Full}(x_i) = 0.9$, $\mu_{Big}(x_i) = 0.1$ and $\mu_{Much}(x_i) = \cdots = \mu_{None}(x_i) = 0$. This makes $Achv(G_i) \geq Full$. The same is assumed for both $Opr(G_i)$ and $Prvn(G_i)$.

We also use the proposition $NULL$ to represent the Null trivially true statement that the status of the satisfaction level of the value property for a goal/cocnstraint is unknown or negative. Meaning that if x_i represents the achievement level of the goal G_i and x_i is unknown or a negative number as per the figure above, then the achievement level of G_i has memberships of $\mu_{Full}(x_i) = \mu_{Big}(x_i) = \cdots = \mu_{None}(x_i) = 0$, and therefore $Achv(G_i) \geq Null$. We also add the $Null$ label to the set of labels $\mathcal{L}$ introduced earlier to make $\mathcal{L} = \{\mathit{Full}, \mathit{Big}, \mathit{Much}, \mathit{Moderate}, \mathit{Some}, \mathit{Little}, \mathit{None}, \mathit{Null}\}$, and $Full > Big > Much > Moderate > Some > Little > None > Null$.

For each value property, we introduce a set of predicates over goals and constraints, where $Full_{achv}(G_i)$ represents $Achv(G_i) \geq Full$, and $Big_{achv}(G_i)$ represents $Achv(G_i) \geq Big$, and so on for all value properties across all the labels part of $\mathcal{L}$. We then introduce a total order where $\forall G \in \mathcal{G} : Full_{achv}(G) \geq Big_{achv}(G) \geq \cdots \geq None_{achv}(G) \geq Null_{achv}(G)$. The same order exists for Opr and $Prvn$ predicates over goals, and the $Achv$ and $Prvn$ predicates over constraints.

In the following sections we will introduce the relations that could exist among goals and constraints within the GCM model, and how the value labels of the goals and constraints nodes will propagate through these relations. It is important to mention here, before we discuss the relations, that for space constraints in this paper, as set by the conference requirements, we will not present the complete set of ground relation axioms for any of the G-G and C-G relations discussed, but rather we will present the propagation rules of the value properties of goals and constraints over these relations. It should be understood that the rules are generated by aggregating/generalizing the extensive ground axioms we started with, for all of the relations. The rules and axioms are tested for soundness and completeness, and available for interested researchers by contacting the author.

IV. Goal-Goal Relations

A. Goal Reduction/Refinement Relations

Goal reduction relations, especially AND/OR ones, are the easiest among the relations that could exist among goals, and the most widely used since the early days of conceptual modeling and AI ([11]). The goal reduction/refinement process, as we said earlier, is responsible for generating the tree like structures found in goal-tree/s. Because of the popularity of this type of relations, we will not expand on it here, except to add few clarifications. In this paper, for simplicity, only binary AND and OR goal reduction relations are considered.This should not be taken as a restriction, in fact any n-ary operator could be used. Since all the operators we use and considered in our framework, such as $\wedge$, $\vee$, $\min$, $\max$, etc., are all associative, and therefore can be used as n-ary operators. And because strategic goals at the top of goals tree are reduced using n-ary operators, we can use such decomposition to propagate meaningful properties (or value labels) of these goals across such relations. *The Propagation Rules of Value Labels using Goal Reduction Relations:*

$$(G_1, G_2) \xrightarrow{and} G : \quad Opr(G) = \min\{Opr(G_1), Opr(G_2)\} \tag{1}$$
$$Achv(G) = \min\{Achv(G_1), Achv(G_2)\} \tag{2}$$
$$Prvn(G) = \max\{Prvn(G_1), Prvn(G_2)\} \tag{3}$$
$$(G_1, G_2) \xrightarrow{or} G : \quad Opr(G) = \max\{Opr(G_1), Opr(G_2)\} \tag{4}$$
$$Achv(G) = \max\{Achv(G_1), Achv(G_2)\} \tag{5}$$
$$Prvn(G) = \min\{Prvn(G_1), Prvn(G_2)\} \tag{6}$$

B. Goal-Gaol Lateral Relations

In this section we introduce a formalization of the G-G lateral relations introduced informally in [10], and briefly mentioned earlier: *Supports*, *Hinders* and *Conflicts-with*. Figure 4 lists 12 possible combinations of cause-effect relations we could have, assuming that the cause comes in the form of reaching either a full or a partial level of one of the three value properties of the *start goal*, or the goal G_1 which is in left side of the lateral relation $G_1 \xrightarrow{lr} G$, and the effect comes in the form of reaching either a full or a partial level of one the three properties for the goal G on the right side of the relationships, the *end goal*.

Those lateral relations are named based on whether the cause/effect is positive (achievement or operationalization) or negative (prevention) of the goal at that end of the relation. For example, if G_1 is achieved fully and this will cause G to be fully achieved as well, then we call the relation: a “$++$” relation; and if having G_1 fully achieve will cause G to be fully prevented, then the relation is called: a “$+-$” relation. And, to differentiate between fullness and partiality effect, we put round brackets around the the sign which represent the effect, if the effect is partial. For example, if achieving G_1 fully will cause G to be partially prevented, then the lateral relation between them will be called: a “$+(-)$” relation, and we represent this relation as: $G_1 \xrightarrow{+(-)} G$.

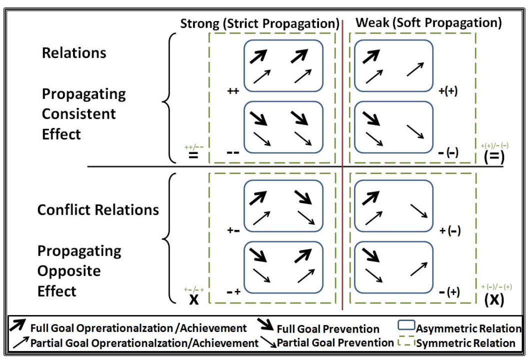

Fig. 4. Goal-to-Goal (G-G) Lateral Relations

Figure 4 shows four lateral relations categorized as *Strong/Strict Lateral Relations*. These relations have the strength level of the cause (operationalization, achievement or prevention in the start goal) match the strength level of the effect on the end goal of the relation. The Strong Lateral Relations include the following relations: “$++$”, “$--$”, “$+-$”, and “$-+$”. On the other hand, the *Weak/Soft Lateral Relations* are relations which propagate a *partial* effect on the end goal of the relation without consideration to the strength level of the cause. In this category of relations, the name of the relation will always have the effect sign between round brackets to show that these relation will not cause severe/full operationalization, achievement or prevention to the goal on the end side of the lateral relation, hence the name. Relations belong to this category are: “$+(+)$”, “$-(-)$”, “$+(-)$”, and “$-(+)$”.

The above mentioned eight lateral relations could be categorized differently. In Figure 4, the lateral relations are split horizontally into two distinct groups. The top group includes relations in which the causes propagate consistently to the relations' effects. In other words, the sign of the cause matches the sign of the effect. The group at the bottom includes relations in which the cause sign is always different than the effect sign, or the opposite of it. Each of these relations represents a conflict among its two goals. If the start goal is achieved, the end goal will be prevented, and viceversa.

A conflict is different than an inconsistency. Conflicts are permitted in ViVD-EKM. We felt the need to allow for representing conflicts because conflicts in the real world are the source of opportunities as we explained and discussed thoroughly in [10]. Therefore, Conflict Relations are supported in Constrained Rationality while inconsistencies are highlighted to be brought to the modelers attention, to be resolved.

Note that eight lateral relations discussed above are all *Asymmetric Lateral Relations*. If an asymmetric relation states that an achievement in the start goal will result on an achievement of the end goal, then it is *not true* that the statement also supports the argument that a prevention of the start goal will result on a prevention of the end goal. Now, let us introduce four *Symmetric Lateral Relations*: “$=$”, “$(=)$”, “$\times$” and “$(\times)$”. Each of these relations is the equivalent of combining two of the Asymmetric Relations listed above. For example “$=$” equivalent to (“$++$” $\cup$ “$--$”),meaning that a full achievement of the start goal will lead to a full achievement of the end goal, and a full prevention of the start goal will lead to a full prevention of the end goal.

We have a set of lateral relations which represent sufficiently any support, hinders or conflicts-with relations that could exist between any two goals in the goal model an agent have. But before listing the propagation rules for G-G Lateral relations, let us first add the concept of a *Modifier* to the lateral relation. So far we used a lateral relation of “$+(+)$” to represent a relation in which a full or partial satisfaction of the source node will make the satisfaction level of the target node be partial. In fact it is like stating that the relation is of “$+(Partial+)$”. The “$Partial$” part of the relation definition is what we call the relation's *Modifier*. The relation's *Modifier* M is a label that belongs to the same set of labels $\mathcal{L}$ used for value properties, i.e. $M \in \mathcal{L}$, where $\mathcal{L} = \{Full, Big, Much, Moderate, Some, Little, None, Null\}$. Note that an assignment of $Null$ as a label to a relation's *Modifier* makes the relation has no effect on the target node, i.e. as if the relation does not exist. *The Propagation Rules of Value Labels using G-G Lateral Relations:*

$$G_1 \xrightarrow{=} G: \quad Opr(G) = Opr(G_1) \tag{7}$$
$$Achv(G) = Achv(G_1) \tag{8}$$
$$Prvn(G) = Prev(G_1) \tag{9}$$
$$G_1 \xrightarrow{(M=)} G: \quad Opr(G) = \min\{Opr(G_1), M\} \tag{10}$$
$$Achv(G) = \min\{Achv(G_1), M\} \tag{11}$$
$$Prvn(G) = \min\{Prvn(G_1), M\} \tag{12}$$
$$G_1 \xrightarrow{\times} G: \quad Opr(G) = Null \tag{13}$$
$$Achv(G) = Prev(G_1) \tag{14}$$
$$Prvn(G) = Achv(G_1) \tag{15}$$
$$G_1 \xrightarrow{(M\times)} G: \quad Opr(G) = Null \tag{16}$$
$$Achv(G) = \min\{Prvn(G_1), M\} \tag{17}$$
$$Prvn(G) = \min\{Achv(G_1), M\} \tag{18}$$
$$G_1 \xrightarrow{++} G: \quad Opr(G) = Opr(G_1) \tag{19}$$
$$Achv(G) = Achv(G_1) \tag{20}$$
$$Prvn(G) = Null \tag{21}$$
$$G_1 \xrightarrow{+(M+)} G: \quad Opr(G) = \min\{Opr(G_1), M\} \tag{22}$$
$$Achv(G) = \min\{Achv(G_1), M\} \tag{23}$$
$$Prvn(G) = Null \tag{24}$$
$$G_1 \xrightarrow{--} G: \quad Opr(G) = Achv(G) = Null \tag{25}$$
$$Prvn(G) = Prev(G_1) \tag{26}$$

$$G_1 \xrightarrow{-(M-)} G: \quad Opr(G) = Achv(G) = Null \tag{27}$$
$$Prvn(G) = \min\{Prvn(G_1), M\} \tag{28}$$
$$G_1 \xrightarrow{+-} G: \quad Opr(G) = Achv(G) = Null \tag{29}$$
$$Prvn(G) = Achv(G_1) \tag{30}$$
$$G_1 \xrightarrow{+(M-)} G: \quad Opr(G) = Achv(G) = Null \tag{31}$$
$$Prvn(G) = \min\{Achv(G_1), M\} \tag{32}$$
$$G_1 \xrightarrow{-+} G: \quad Achv(G) = Prev(G_1) \tag{33}$$
$$Prvn(G) = Opr(G) = Null \tag{34}$$
$$G_1 \xrightarrow{-(M+)} G: \quad Achv(G) = \min\{Prvn(G_1), M\} \tag{35}$$
$$Prvn(G) = Opr(G) = Null \tag{36}$$

V. Constraint-Goal Relations

Constraints also could affect goals. Constraints are connected to goal nodes through Constraint-Goal (C-G) Lateral Relations, which are exactly similar to the G-G Lateral ones. Therefore, the Propagation Rules of Value Labels using C-G Lateral Relations are similar to ones introduced above, with one exception: constraints do not have Operationalization value and do not affect the Operationalization value of the target goal node it is affecting (connected to it using the lateral relation).

VI. Constrained Rationality Qualitative Forward Reasoning Framework

We talked about how the value labels of goals propagate or get affected along individual relations, whether G-G relations or C-G relations, but we did not yet discussed how all these relations sinking into the goal node, or fanning out from the goal node, will affect the overall value labels of each of the goal nodes. Let $\mathcal{R}_{G-G} \subseteq \mathcal{R}$, where $\mathcal{R}_{G-G}$ is the set of relations in $\mathcal{R}$ that includes all goal reductions and goal-to-goal lateral relations which exist in $\mathcal{R}$; and $\mathcal{R}_{C-G} \subseteq \mathcal{R}$, where $\mathcal{R}_{C-G}$ is the set of relations in $\mathcal{R}$ that includes all constraint-goal lateral relations in $\mathcal{R}$. And, let $(\mathcal{R}_{G-G} \cap \mathcal{R}_{C-G}) = \varnothing$ and $(\mathcal{R}_{G-G} \cup \mathcal{R}_{C-G}) = \mathcal{R}$. For each goal $G_i \in \mathcal{G}$, let: the set of G-G relations (reduction and lateral) that targets/ends-with G_i is the set $\mathcal{R}_{G-G_i} \subseteq \mathcal{R}_{G-G}$; the set of C-G lateral relations that targets/ends-with G_i is the set $\mathcal{R}_{C-G_i} \subseteq \mathcal{R}_{C-G}$; and $Achv_r(G_i)$, $Opr_r(G_i)$, and $Prvn_r(G_i)$ are the value labels of the goal G_i as a result of the relation r. The final values labels of G_i at any time t are concluded by the following propagation rules:

$$Opr(G_i) = \left(Opr(G_i) \vee \bigvee_{r_j \in \mathcal{R}_{G-G_i}} Opr_{r_j}(G_i) \right) \tag{37}$$
$$Achv(G_i) = \left(Achv(G_i) \vee \bigvee_{r_j \in \mathcal{R}_{G-G_i}} Achv_{r_j}(G_i) \right) \wedge \left(\bigwedge_{r_k \in \mathcal{R}_{C-G_i}} Achv_{r_k}(G_i) \right) \tag{38}$$
$$Prvn(G_i) = \left(Prvn(G_i) \wedge \bigwedge_{r_j \in \mathcal{R}_{G-G_i}} Prvn_{r_j}(G_i) \right) \vee \left(\bigvee_{r_k \in \mathcal{R}_{C-G_i}} Prvn_{r_k}(G_i) \right) \tag{39}$$

Figure 5 shows that the effect on any goal's achievement (and operationalization), based on all G-G relations whether reduction or lateral targeting the goal is maximized, while the goal's prevention is minimized. This follows the same rules of the OR reduction relation introduced earlier. At the same time, C-G lateral relations plays a role of limiting (minimizing) the goal's achievement to a limit set by the relation if it has positive effect on the goal, or increasing the goal's prevention level to match one set by the constraint if the constraint has a negative effect on the goal. The constraints effect follows the same rules of ANDing two goals' values, but here with two values of the same goal: the first is the original value before the constraint effect and the second is the value after the constraint effect. The AND relation rules are introduced earlier.

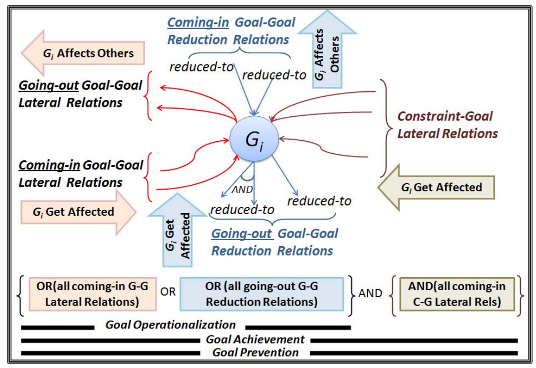

Fig. 5. Dealing with multiple Goal-Goal and Constraint-Goal Relations coming-in to a Goal Node or going-out from it

Goals' Value Labels Forward Propagation Algorithm: Let there be four arrays: *Initial_C* is an array that holds the value-labels of $\langle Achv(C_i), Prvn(C_i)\rangle$ for each C_i belongs to $\mathcal{C}$ part of the GCM model graph $\langle \mathcal{G}, \mathcal{C}, \mathcal{R}\rangle$; *Initial_G* is an array that holds the value-labels of $\langle Opr(G_j), Achv(G_j), Prvn(G_j)\rangle$ for each G_j belongs to $\mathcal{G}$ part of the GCM model graph $\langle \mathcal{G}, \mathcal{C}, \mathcal{R}\rangle$; *Previous_G* hold the previous value-labels for each G_i as per the last run of the propagation algorithm loop; and *Current_G* hold the current value-labels for each G_i, as per the current run of the algorithm. The number of elements for *Initial_C* is $|\mathcal{C}|$; and for each of *Initial_G*, *Previous_G* and *Current_G* is $|\mathcal{G}|$; Now, we introduce the following value-label forward propagation algorithm:

```
value-label-array Label_GCM_Goals(GCM_Graph⟨𝒢,𝒞,ℛ⟩, c-value-label-array Initial_C, value-label-array Initial_G)
// Start with the Goals value-labels given in Initial_G
Curren_G=Initial_G

repeat
   Previous_G=Current_G
   // For every Goal, apply all Relations feeding into it
   for all G_i ∈ 𝒢 do
      //OR all Goal-to-Goal Relations coming to G_i
      for all R_j ∈ ℛ_{G−G} such that end_goal(R_j) == G_i do
         Opr = Apply_G_to_G_Opr_Rules(G_i, R_j, Previous_G)
         Achv = Apply_G_to_G_Achv_Rules(G_i, R_j, Previous_G)
         Prvn = Apply_G_to_G_Prvn_Rules(G_i, R_j, Previous_G)
         //OR with the effect of all previous G-G Rel affected G_i so far
         Current_G[i].Opr = max(Opr, Previous_G[i].Opr)
         Current_G[i].Achv = max(Achv, Previous_G[i].Achv)
         Current_G[i].Prvn = min(Prvn, Previous_G[i].Prvn)
      end for

      //AND all Constraint-to-Goal Relations coming to G_i
      for all R_k ∈ ℛ_{C−G} such that end_goal(R_k) == G_i do
         Achv = Apply_C_to_G_Achv_Rules(G_i, R_k, Initial_C)
```

Prvn = *Apply_C_to_G_Prvn_Rules*(G_i, R_k, *Initial_C*)
//AND with the effect of all previous G-G/C-G Rel affected G_i so far
Current_G[i].Achv = min(*Achv, Previous_G[i].Achv*)
Current_G[i].Prvn = max(*Prvn, Previous_G[i].Prvn*)
end for
end for
until (*Current_G==Previous_G*)

return *Current_G*

A note worth mentioning about the algorithm termination: the formulas in our framework are all propositional Horn Clauses. This means that deciding if a ground assertion holds not only decidable, but also decidable in polynomial time [12], [13]. It could be easily proved that the algorithm will terminate after at most $24|\mathcal{G}|+1$ loops. In reality, it will terminate after much less than this ceiling, because many updates to the value variables will happen in parallel.

CM Mobilize a Plan to Accept Government Bailout

	Initial		run 1		run 2		run 3		run 4		run 5	
	Achv	Prvn	Achv	Prvn	Achv	Prvn	Achv	Prvn	Achv	Prvn	Achv	Prvn
G0							L		O	M	O	M
G1					L		O		O		O	
G2					O		O	M	O	M	O	M
G3				B		B	L	B	L	B	L	B
G4					O		O		O		O	
G5	M		M		M		M		M		M	
G6	F		F		F		F		F		F	
G7			O		O	M	O	M	O	M	O	M
G8					O		O		O		O	
G9			L	S	L	S	L	S	L	S	L	S
G10												
G11			O		O		O		O		O	
G12												
G13				O		O		O		O		O
G14				O		O		O		O		O
G15			O		O		O		O		O	
G16-18												
G19	L		L		L		L		L		L	
G20	O		O		O		O		O		O	
G21			L		L		L		L		L	
G22				F		F		F		F		F
G23	O		O	F	O	F	O	F	O	F	O	F
G24			L	M	L	M	L	M	L	M	L	M
G25												
G26	F		F		F		F		F		F	
G27	S		S		S		S		S		S	
G28	O		O		O		O		O		O	
G29												
G30				F		F		F		F		F
G31-35												
G36	L		L	F	L	F	L	F	L	F	L	F
G37												
G38	L	M	L	M	L	M	L	M	L	M	L	M

C1-C6	F	

Constraints' Initial Values

CM Mobilize a Plan to Reject Bailout & Declare Bankrupcy

	Initial		run 1		run 2		run 3		run 4		run 5	
	Achv	Prvn	Achv	Prvn	Achv	Prvn	Achv	Prvn	Achv	Prvn	Achv	Prvn
G0							L		O		O	
G1					L		O		O		O	
G2					O		O		O		O	
G3				B		B	L	B	L	B	L	B
G4					O		O		O		O	
G5	M		M		M		M		M		M	
G6			F		F		F		F		F	
G7			O		O		O		O		O	
G8					O		O		O		O	
G9			L	S	L	S	L	S	L	S	L	S
G10												
G11			O		O		O		O		O	
G12												
G13				O		O		O		O		O
G14				O		O		O		O		O
G15			O		O		O		O		O	
G16-18												
G19	L		L		L		L		L		L	
G20	O		O		O		O		O		O	
G21			L		L		L		L		L	
G22												
G23	O		O		O		O		O		O	
G24			L	M	L	M	L	M	L	M	L	M
G25	F		F		F		F		F		F	
G26												
G27	S		S		S		S		S		S	
G28	O		O		O		O		O		O	
G29												
G30				F		F		F		F		F
G31-35												
G36	L		L		L		L		L		L	
G37												
G38	L	M	L	M	L	M	L	M	L	M	L	M

C1-C6	F	

Constraints' Initial Values did not change (Same Realities)

Labels:	Full F	Big B	Much M	Moderate Some S	Little L	None N	Null

Fig. 6. Algorithm Runs for the CM Example

VII. Experimental Results and Conclusion

In the CM's example which was presented earlier, analyzing the effect of a plan by which CM accepts a government bailout with conditions limiting it from outsourcing to cut operational cost on the long run, and based on the hypothetical GCM model shown earlier, we found that CM is better off rejecting the bailout and instead operationalize the bankruptcy goal by declaring bankruptcy (assuming bankruptcy will provide full achievement of goal G_6 by allowing restructuring of CM current debt). The algorithm runs for both scenarios (using initial values representing each scenario, and for simplicity assuming operationalizability equals achievability for all goals) are shown in Figure 6. As shown, the bailout will have a prevention effect on the long-term prosperity goal, an effect that the bankruptcy will not have. The experiment, even though simplified to fit this paper space and need, demonstrates the complexity of strategic decision making, knowing the interdependency and interrelations goals and constraints have among them, and how the reasoning framework we proposed can help identify the effect of adopting certain plans/goals on the ultimate (conflicting) strategic goals the agent has.

In this paper, we presented a formal qualitative goals and constraints reasoning framework for strategic decision making. We looked at the many types of relations that could exist among goal and constraint nodes, and how value labels of the goal value properties propagate through these relations. We proposed a value label forward propagation algorithm which can conclude the final value labels for each goal node within the GCM model, based on initial set of values defined by the effect a plan has on goals and constraints. And while we have tested the framework with success on classical game theory conflicts, such as the prisoners' dilemma and the game of Chicken, and other one-agent and multi-agent conflicts, we still need to conduct further testing on bigger (preferably real) conflicts and strategic decision making situations. We are also in the process of incorporating other value properties to track and use priorities, order and emotions that agents have, as well as using and extending game theory's stability analysis concepts.

References

[1] M. Wooldridge, *Reasoning About Rational Agents*. MIT Press, Cambridge, Massachusetts, 2000.
[2] L. Braubach, A. Pokahr, D. Moldt, and W. Lamersdorf, "Goal representation for BDI agent systems," in *Second International Workshop on Programming Multiagent Systems: Languages and Tools*, vol. 7. Springer, 2004, pp. 9–20.
[3] E. Yu, "Modeling Strategic Relationships For Process Reengineering," Ph.D. dissertation, Computer Science Department, University of Toronto, 1995.
[4] A. Dardenne, A. van Lamsweerde, and S. Fickas, "(1993). Goal-directed Requirements Acquisition," *Science of Computer Programming*, vol. 20, pp. 3–50, 1993.
[5] J. Mylopoulos and J. Castro, "Tropos: A Framework for Requirements-Driven Software Development," *Information Systems Engineering: State of the Art and Research Themes, Springer-Verlag*, pp. 261–273, 2000.
[6] M. Winikoff, J. Harland, and L. Padgham, "Linking Agent Concepts and Methodology with CAN," in *Submitted to the First International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS 2002)*, 2002.
[7] M. Winikoff, L. Padgham, J. Harland, and J. Thangarajah, "Declarative & Procedural Goals in Intelligent Agent Systems," in *Proceedings of the Eighth International Conference on Principles of Knowledge Representation and Reasoning*, 2002, pp. 470–481.
[8] P. Giorgini, J. Mylopoulos, and R. Sebastiani, "Simple and Minimum-Cost Satisfiability for Goal Models," in *Proceedings of International Conference on Advanced Information Systems Engineering*, vol. 4, 2004, pp. 20–33.
[9] P. H. Shaw and R. H. Bordini, "Towards Alternative Approaches to Reasoning about Goals," in *Proceedings of 5th International Workshop on Declarative Agent Languages and Technologies, held with the 6th International Joint Conference of Autonomous Agents and Multi Agent Systems*. Springer, 2007, pp. 104–121.
[10] M. M. Al-Shawa, "Viewpoints-based Value-Driven - Enterprise Knowledge Management (ViVD-EKM). MASc Thesis, Electrical and Computer Engineering Department, University of Waterloo," 2006.
[11] N. Nilsson, *Problem-solving methods in artificial intelligence*. McGraw-Hill Pub. Co., 1971.
[12] A. Horn, "On sentences which are true of direct unions of algebras," *Journal of symbolic logic*, pp. 14–21, 1951.
[13] W. Clocksin and C. Mellish, *Programming in Prolog: Using the ISO Standard*. Springer-Verlag, 1984.