**Mars Analyst's Guide**

Mars Simulation Infrastructure Library, V2.10

October, 2012

William H. Duquette

[William.H.Duquette@jpl.nasa.gov](mailto:William.H.Duquette@jpl.nasa.gov)

Jet Propulsion Laboratory

*Copyright 2008-2012, by the California Institute of Technology. ALL RIGHTS RESERVED. United States Government Sponsorship acknowledged. Any commercial use must be negotiated with the Office of Technology Transfer at the California Institute of Technology.*

*This software is subject to U.S. export control laws and regulations and has been classified as EAR99. By accepting this software, the user agrees to comply with all applicable U.S. export laws and regulations. User has the responsibility to obtain export licenses, or other export authority as may be required before exporting such information to foreign countries or providing access to foreign persons.*

Models 4

1. Introduction 5

1.1 Other Mars Documents 5

2. Mars Concepts 6

2.1 The Client Simulation 6

2.2 MAM: Modeling Belief Systems 6

2.3 GRAM: Modeling the Population 6

2.4 The Playbox 6

2.5 Groups 7

2.5.1 Civilian Groups 7

2.5.2 Force Groups 8

2.5.3 Organization Groups 8

2.6 Simulated Time 8

3. Mars Affinity Model 9

3.1 Belief Systems Defined 9

3.1.1 Topics 9

3.1.2 Positions 10

3.1.3 Emphasis 11

3.1.4 Belief Systems 11

3.2 Modeling Affinity 12

3.2.1 Desired Properties 12

3.2.2 Definitions 13

3.2.3 The Basic Model 14

3.2.4 Handling Ambivalence 15

3.2.5 Implicit Commonality 15

3.2.5.1 Adding Implicit Topics 16

3.2.5.2 Playbox Commonality 16

3.2.5.3 The Playbox Commonality Dial 17

3.2.5.4 Summary 17

3.2.6 Are the Properties Met? 18

3.3 Computing Affinity 19

3.3.1 Definitions 19

3.3.2 The Cases 19

4. Generalized Regional Attitude Model 21

4.1 Attitude Curves 21

4.1.1 Level Effects 22

4.1.1.1 Level Effects Defined 22

4.1.1.2 Effect of Epsilon on Level Effects 24

4.1.2 Slope Effects 24

4.1.2.1 Slope Effects Defined 24

4.1.2.2 Situations and Slope Chains 25

4.1.2.3 Effects of Epsilon on Slope Effects 26

4.1.3 Ascending and Descending Thresholds 26

4.1.4 Scaling of Contributions 27

4.1.5 Causes and Scaling 28

4.2 Neighborhoods and Groups 29

4.3 Satisfaction 29

4.3.1 Satisfaction Levels 29

4.3.2 Concerns 30

4.3.3 Composite Satisfaction, Weights, and Saliencies 31

4.3.4 Trends 32

4.4 Cooperation 33

4.4.1 Cooperation Levels 33

4.4.2 Composite Cooperation 33

4.5 Drivers, Inputs, and Effects 34

4.5.1 Neighborhood Proximities 34

4.5.2 Proximity Limits 36

4.5.3 Neighborhood Effects Delay 36

4.5.4 Satisfaction Influence 36

4.5.5 Cooperation Influence 37

4.5.6 Here, Near, and Far Factors 38

4.5.7 Computing Spread 38

4.6 Dynamic Civilian Groups 39

4.6.1 Use Cases 39

4.6.2 Dynamic Operations 40

4.6.3 Moving a Group 40

4.6.4 Splitting a Group 41

4.6.5 Transfer Population between Groups 41

4.6.6 Pending Attitude Effects 42

4.6.7 Dead Groups and Neighborhoods 43

4.7 History 44

5. Relationship Multiplier Functions 45

5.1 Nominal Relationships 45

5.2 Specific Relationship Multiplier Functions 46

6. Miscellaneous Models and Algorithms 48

6.1 Z-Curve Functions 48

6.2 Poisson Processes 48

6.3 Selecting a Random Location in a Neighborhood 49

Appendices 50

7. Acronyms 51

# Models

## Introduction

This document presents the models and related constructs implemented by version 2.10 of the Mars Simulation Infrastructure Library (Mars). The models are described in sufficient detail to allow implementation; the implementation itself is not in the scope of this document.

### Other Mars Documents

The Mars documentation set may be found in the “mars/docs” directory of the Mars build tree; open “mars/docs/index.html” in a web browser, and follow the links. The documentation is usually included in the documentation set for client simulations. Otherwise, documents can be obtained directly from the JNEM or Athena projects; contact [David.R.Hanks@jpl.nasa.gov](mailto:David.R.Hanks@jpl.nasa.gov) or [William.H.Duquette@jpl.nasa.gov](mailto:Willam.H.Duquette@jpl.nasa.gov). Note that this document is also available in hardcopy.

*Software Manual Pages*

Extensive documentation of the Mars software tools and libraries is included in the software source tree in the form of software “man pages”.

## Mars Concepts

This section gives an overview of Mars and the concepts shared by its various models. The discussion is kept to a high level; see Sections 3 and following for detailed models.

### The Client Simulation

Mars is an infrastructure library; its models are intended for use in other simulation applications. These are referred to as *client simulations*, or simply as *clients*.

### MAM: Modeling Belief Systems

MAM, the Mars Affinity Model, models the *belief systems* of entities, e.g., *civilian groups*, and from them computes *affinities* which are the basis for *relationships*. MAM is described in detail in Section 3.

### URAM: Modeling the Population

The Unified Regional Attitude Model (URAM) is a population dynamics model of the attitudes and behavior of groups within neighborhoods within the playbox. URAM tracks changes in attitudes over time. Changes are driven by events and situations modeled within the client simulation (e.g., civilian casualties, presence of force units in a neighborhood, and so forth). The client simulation uses algorithms and rule sets to analyze these *drivers* and provide attitude inputs to URAM.

The effects of an attitude driver are not necessarily limited to the neighborhood and group that are directly affected by the driver—for certain kinds of attitude there may be second order effects on other groups in the neighborhood, and on groups in other neighborhoods. These *indirect effects* generally weaken with distance.

As simulation time progresses, URAM tracks the contribution of each driver to each attitude curve, thus enabling the significant drivers to be determined after the fact.

At present, URAM supports four different types of attitude curve: the *cooperation* of a civilian group with a force group, the *satisfaction* of a civilian group with respect to various *concerns*, the *horizontal relationship* of one group with another, and the *vertical* relationship of a group with an actor.

URAM has two major components: the URAM curve manager, which defines a general model and framework for attitude curves, and URAM proper, which defines the specific types of attitude curve listed above. The URAM curve manager is described in Section 4, and URAM proper is described in Section 5.

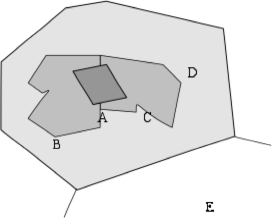
#### History

URAM is a generalization, extension and revision of the Generalized Regional Analysis Model (GRAM) developer for use by the Joint Non-kinetic Effects Model (JNEM) and by the Athena Stability and Recovery Operations simulation. GRAM was a generalization and extension of JRAM, also developed for JNEM, which was in turn based on an earlier model called the Regional Analysis Model, or RAM. RAM was developed for the National Simulation Center by the Texas A&M University’s Department of Political Science, working with the George Bush School of Government and Public Service and the Texas Center for Applied Technology (both also at Texas A&M). RAM was part of the Spectrum Simulation to model biases, alliances, rivalries, and other aspects of inter-group relationships.

URAM was designed specifically for use in version of the Athena S&RO simulation. It supports longer time horizons explicitly, and models variation in horizontal and vertical relationships as well as satisfaction and cooperation.

### The Playbox

URAM models population dynamics in a geographical region called the *playbox*. The playbox is divided into areas called *neighborhoods*. Neighborhoods are simply a way of dividing the playbox into a number of reasonably homogeneous areas, and may be of any size: country, province, city, town, zip code, and neighborhood proper. Geographically, neighborhoods are usually defined as polygons whose vertices are defined by map coordinates; however, this is the province of the client simulation. In the diagram below, “A” is an urban area surrounded by suburban areas B and C; all three lie within D, a county, which abuts E, another county.



Events in the client simulation can have attitude effects in URAM; these effects take place within neighborhoods, and affect the population of the neighborhoods. The geographic *spread* of the ripple effects of an event taking place in a neighborhood depends on how nearby other neighborhoods are presumed to be—not simply geographically but also socially. The nearness of one neighborhood to another is called the *neighborhood proximity*. There are four proximity levels: *here*, *near*, *far*, and *remote*. The diagram above shows proximity to neighborhood A. From A’s point of view, A is here. Suburbs B and C are *near* A, and outlying area D is *far* from A. Neighborhood E is *remote*.[[1]](#footnote-1) An event in A would affect A immediately, would likely affect B and C, though to a lesser degree, might affect D to a much lesser degree, and would not affect E at all. Ripple effects in other neighborhoods can also be delayed by an interval, which is an input for each pair of neighborhoods.

### Groups

The people in the playbox are divided into *groups*, of which there are three kinds: civilian groups, force groups, and organization groups. URAM models the horizontal relationships (positive or negative) between pairs of groups as these relationships change over time in response to events and situations.

#### Civilian Groups

Civilian groups represent the population of the playbox, i.e., the people who actually live in the neighborhoods. This population maybe broken into groups by ethnicity, religion, language, social class, political affiliation, or any other demographic criteria the analyst deems necessary. Groups are similar to the “market segments” used to target advertising: a group is a collection of people who may be assumed to have similar biases, interests, and behaviors due to their demographic similarity. Civilian groups are usually united by their belief systems.

Each civilian group resides in a neighborhood, and each neighborhood must contain at least one civilian group.

URAM models the satisfaction of civilian groups with respect to various concerns, and the cooperation level of civilian groups with force groups, tracking these attitudes as the group members are affected by events and situations taking place in the client simulation. These attitudes then will typically affect the groups' reactions and responses in the client simulation.

#### Force Groups

Force groups represent military forces, such as the U.S. Army, and other groups whose purpose is to apply force. URAM models the level of *cooperation* (i.e., information sharing) of civilian groups with force groups.

#### Organization Groups

Organization groups represent organizations that are present in the playbox to help the civilians. There are three kinds: Non-Governmental Organizations (NGOs), International or Inter-governmental Organizations (IGOs), and Contractors (CTRs). NGOs are groups like the Red Cross or Doctors Without Borders who do humanitarian relief, development, and so forth. IGOs are international organizations like UNESCO. Contractors are commercial firms who are doing development work in the playbox, often but not necessarily working for the Coalition. Organizations may be either local or foreign.

### Actors

In addition to groups, there are also *actors*: significant decision makers within the playbox. URAM models the vertical relationship (positive or negative) of groups with actors as these relationships change over time in response to events and situations.

### Simulated Time

Mars measures simulated time in integer *ticks*. The duration of one tick can be anything from one second to two minutes to three hours to four or more days; tick sizes of one minute and of one day are typical. The simclock(n) module tracks simulated time, and converts between ticks and hours, minutes, and seconds; it also supports military “Zulu-time” strings.

The URAM model, however, is designed explicitly for a time step of a week.

Client simulations will often have a minor time step, the tick, and also one or more major time steps; these are accordingly called *tocks*. In JNEM, for example, the tick is one minute, and GRAM is advanced at the tock, once every five ticks.

## Mars Affinity Model

Athena and JNEM rely heavily on the concept of the horizontal relationship between two groups *f* and *g*, where . Athena also defines the vertical relationship between a group *g* and an actor *a*, where . Because relationships are pair-wise, a large scenario can have thousands or tens of thousands of them. The analyst can enter all of these values, but this is slow, tedious, and error-prone, even presuming that the analyst can determine what all of the relationships should be.

It seems that the nature of a group’s relationships should be due to something about the groups involved. Positive relationships are due to shared cultures, values, and aims; negative relationships are due to opposed cultures, values, and aims. It seems reasonable, then, that if we could characterize the significant cultures, values, and aims of the groups in a region, and then rate each group with respect to each of them, that we could use that as a basis to compute some notion of relationship between the two groups.

Given two groups *f* and *g*, then, we define the *affinity* of group *f* for group *g* to be the natural degree of relationship between the two groups given their particular *belief systems*. Affinity is denoted , where . The relationship used by a client simulation might then be exactly equal to this affinity, or might be a function of it.

This section describes a model of belief systems and a method of computing affinities from them. I will speak primarily in terms of the affinity of one group for another; however, the discussion applies equally well to affinities between groups and actors.

### Belief Systems Defined

We must characterize the values, aims, cultures, and beliefs of each group, so that we can compare them.

#### Topics

First, we define a set of *topics* numbered from 1 to *N*. Each topic represents some issue, value, cultural belief, aim, etc., that is significant in the region of interest. Topics must be stated in absolute terms so that they can be compared across groups. The statement “My party should control the government” is a relative statement, for example; group *f’*s opinion on this topic will mean something different than group *g’*s. The statement “Party X should control the government” is an absolute one, and is something about which *f* and *g* can have opinions that can be meaningfully compared.

#### Positions

Then, let be the *position* of group *f* with respect to topic *i*, where A position indicates where the group stands on the topic. A position of 1.0 indicates strong support; a position of –1.0 indicates strong opposition.

The magnitude of a position,

is called the *strength* or *zeal* of the position, and indicates the extent to which group *f* will take action in the public sphere in support of their position. It does *not* indicate group *f’*s certainty or firmness of belief. For example, it might be that group *f* despises vanilla ice cream but is sent into transports of ecstasy by chocolate ice cream. Unless these preferences lead to significant action in the public sphere, however, group *f’*s position on both flavors should be 0.0.

For groups, we can interpret as the position of the group as an aggregate, without making any assumptions as to how homogenous or heterogeneous the positions of the members of the group are, or whether any particular individual’s position matches that of the group as a whole.

For actors, perception is more important than reality. An actor’s professed beliefs may differ from his privately held beliefs; and it may be further modified by his actions, if they are inconsistent with his professed beliefs.

We will frequently use the following scale when dealing with position values[[2]](#footnote-2):

|  |  |  |
| --- | --- | --- |
| **Symbol** | **Name** | **Value** |
| P+ | Passionately For | 0.9 |
| S+ | Strongly For | 0.6 |
| W+ | Weakly For | 0.3 |
| A | Ambivalent | 0.0 |
| W– | Weakly Against | –0.3 |
| S– | Strongly Against | –0.6 |
| P– | Passionately Against | –0.9 |

#### Emphasis

The positions capture group *f’*s beliefs about particular topics; but to see how group *f* feels about group *g* based on their beliefs, we need to know how group *f* responds to disagreement. We define to be group *f’*s *emphasis* on agreement or disagreement with respect to topic *i*, where .

If is near 1.0, then group *f* puts its emphasis on agreement for topic *i*; agreement on the topic will drive affinity up and disagreement will be discounted. If is near 0.0, then group *f* puts its emphasis on disagreement; disagreement will drive affinity down, and agreement will be discounted.

The original concept used the term “tolerance for disagreement” rather than “emphasis”. In the process of defining affinity we tried several different ways of making affect the computed affinities before finding a formula with reasonable behavior; and in the process of explaining the model to others we found that “tolerance” is a loaded word and did not convey the meaning we intended. The current term was chosen to be both neutral and descriptive of the parameter’s role in the computation.

We will frequently use the following scale when dealing with emphasis values[[3]](#footnote-3):

|  |  |  |
| --- | --- | --- |
| **Symbol** | **Name** | **Value** |
| ASTRONG | Agreement—Strong | 0.90 |
| AWEAK | Agreement | 0.70 |
| NEITHER | Neither | 0.50 |
| DWEAK | Disagreement | 0.35 |
| DSTRONG | Disagreement—Strong | 0.25 |
| DEXTREME | Disagreement—Extreme | 0.15 |

#### Belief Systems

The values of and for all *i* are said to constitute group *f’*s belief system.

### Modeling Affinity

#### Desired Properties

Our formula for computing should have the following properties:

* Relationships of –1.0 are pathological; should only be –1.0 for pathological inputs.
* Affinities should be asymmetric, because different things are important to different groups. Group *f’*s affinity for *g* depends on the topics that are most important to *f*, while *g’*s affinity for *f* is based on the topics that are most important to *g*. Therefore, need not equal , and usually won’t.
* If the group *f’*s position on topic *i* differs in sign from group *g’*s position, that’s a stronger disagreement than if they do not differ in sign, even if the absolute magnitude of the difference is the same. Consider +0.5 and +0.3 vs. +0.1 and –0.1. In the first case the groups differ in the degree of their support; in the latter, one group supports and the other does not. The absolute difference is 0.2 in either case.
* Strong disagreement should not yield indifference. That is, if groups *f* and *g* disagree strongly on one or more topics, should not be 0.0.
* Zealots should distrust the lukewarm. If group *f’*s position on *i* is strong and group *g* agrees only weakly with *f* about *i,* then topic *i* should reduce the affinity between *f* and *g*.
* The lukewarm might admire the zealots. The strength of the zealot’s zeal might increase the affinity of a less zealous group for them.
* The ambivalent should distrust the zealots. Even if group *f’*s position on a topic is 0.0, the group might still be nervous about those who feel strongly about the topic one way or the other, and thereby have a lower affinity with such groups than they otherwise would.[[4]](#footnote-4)
* should be generally continuous for small changes in any input.
* The value of should be reasonable even when the number of topics is 1.

#### Definitions

Given *N* topics numbered , and two groups *f* and *g*, let be group *f’*s position on topic *i*, and let be group *f’*s emphasis on agreement vs. disagreement, as defined in Section 3. Then, we make the following additional definitions.

First, we define the sign and strength of the positions:

Group *f’*s affinity for group *g* will depend on the extent to which they agree or disagree about each topic. Thus, we next define agreement and disagreement metrics for groups *f* and *g* and all topics *i*. The agreement metric, , is defined as follows:

If *f* and *g*’s positions differ in sign, then they do not agree; their agreement is 0.0. Otherwise, we compute their agreement as the geometric mean of their positions. This has several useful properties:

* has the same “units” as .
* If or is 0.0, then there is no agreement; .
* If , then .
* Agreement is symmetrical. (Affinity will not be.)

In other words, if two groups are both lukewarm about a topic, their agreement will be lukewarm; if the two groups are passionate about the topic, their agreement will also be passionate. If one is passionate and one is lukewarm, their agreement will be somewhere in the middle. And if they do not agree at all, their agreement is 0.0.

The geometric mean is much better than the arithmetic mean in this case. Suppose that is 1.0, but is 0.0. The arithmetic mean would give an agreement of 0.5, which is absurd given that *g* is completely ambivalent about the topic. The geometric mean gives an agreement of 0.0 in this case.

Next, the disagreement metric, , is defined as the average difference in their positions:

Again, this has several useful properties:

* has the same “units” as ; thus, agreements and disagreements are comparable.
* Disagreement is symmetrical. (Affinity will not be.)

Next, we define the emphasis ratio:

This value is used to magnify the importance of disagreements. If is 1.0 (a perfect emphasis on agreement) then is 0.0 and disagreements on topic *i* don’t matter to *f*. As approaches zero, gets larger and larger until, in the pathological case of , disagreement on topic *i* will dominate the result.

#### The Basic Model

Intuitively, the affinity between groups *f* and *g* is increased by agreements and decreased by disagreements, as modified by the emphasis that *f* puts on agreements and disagreements. If we were to compute the affinity between the two groups using only one topic *i*, we could define it like this:

The denominator normalizes the result so that .

The affinity of *f* with *g* given all topics should clearly be some kind of weighted average of the ’s. Now , the strength of *f’*s position on *i*,is precisely how important topic *i* is to *f* relative to other topics; hence, is a natural weight. Normalizing, this gives us the following equation:

This equation has several special cases that would result in division by zero, and which therefore require special handling:

* As mentioned above, is undefined when is 0.0; there are several distinct cases.
* The denominator will be 0.0 if is 0.0 for all *i*.

We will address the special cases in the final version of the model.

#### Handling Ambivalence

One of our requirements is that the ambivalent will distrust the zealous, that is, if is 0.0 and is high, then group *f*’s affinity for *g* will tend to decrease. At present it does not, because we use the ’s as the weights in our weighted average, and topics for which is zero drop out.

We used the ’s as the weights because we wished to weigh the agreements and disagreements by the importance of the topics to group *f*. What we now see is that doesn’t adequately capture that importance. In fact, a topic can be important because of the strength of *f*’s belief, or because of the strength of the disagreement.

Hence, we define to be the importance of topic *i* to group *f* in the context of group *g*’s belief system, where

In short, strong disagreements trump weak zeal. The equation for then becomes

or, equivalently,

This new formula has all of the desired properties of its predecessor, and also allows the ambivalent to distrust the zealous.

#### Implicit Commonality

While working with the two versions of the model described above, we noticed two problems:

* Affinity numbers were lower than we expected, and were frequently negative.
* The computed affinity was very sensitive to the number of topics.

We determined that the problem was with our selection of topics. When defining topics for a region, it is natural to focus on the topics for which there is disagreement; we were defining many such topics, but were omitting topics on which most of the entities agree. In short, we were neglecting the *cultural commonality* of the groups in the playbox.

##### Adding Implicit Topics

We realized that commonality could be handled by adding some number of implicit topics on which there is general agreement. Thus, we assume that there are some common topics not included in the list of specific topics. Let us assume further, and without loss of generality, that the two groups are in complete agreement on these topics, and are extremely passionate. That is, they have the same positions, and their zeal is 1.0.

If these topics were added to the affinity calculation, they would insert an additive term in the numerator and an identical term in the denominator. This leads to the following redefinition of :

where is the number of implicit topics of agreement between *f* and *g*. If is 0, we have the same model we had before. As increases, so does the implicit commonality of the two groups. When , implicit commonality balances the explicit topics; when , the explicit topics dominate, and when , the implicit commonality dominates.

##### Playbox Commonality

It is clear that cannot be an input to the model; it is a pairwise value, and one of the reasons for defining the affinity model is to avoid such pairwise inputs. Consequently, let us define as the cultural commonality within the playbox, and as group *f*’s share in that common culture, where . If group *f* belongs to the dominant culture in the playbox, then . If group *f* is a complete outsider, then . Then we can define as follows:

If *f* and *g* are both members of the dominant culture, then they will get all of the playbox commonality; if either is an outsider, they will get none of it.

However, doesn’t make a good input, either; ideally it ought to depend on . So let

, for

Set to 1 for members of the dominant culture, and to 0 for complete outsiders. We can then define

##### The Playbox Commonality Dial

Our formulation of does a good job of adding implicit commonality to the model. However, there is the related problem that is very sensitive to the number of topics. We can handle this by tying to the number of explicit topics as follows:

for

The input is then our commonality dial. It can default to 1.0, where implicit topics exactly balance explicit topics, and be adjusted up and down by the user. Increasing or decreasing will tend to increase or decrease affinities across the board, to the extent that the groups involved participate in the playbox commonality.

has another useful property—the analyst can set the playbox commonality and then add or delete topics without needing to adjust it, because retains its meaning as the number of topics changes.

#### Relevance of Topics

In the real world, some topics have more relevance than others. In country X, for example, suppose that the groups in the region have strong beliefs about the desirability of U.S. intervention in that region. Some are strongly for it; others are strongly opposed. This is a significant fault line. Suppose, however, that such intervention is entirely hypothetical. The U.S. has not intervened in living memory, and no one in the country has any reason to expect that it might in the foreseeable future. In this case, it's unlikely that the topic "U.S. Intervention" is going to have a significant effect on affinities. The topic is not relevant.

If the U.S. announced that it was likely to bring troops to the country for some reason, then this topic would suddenly become relevant, and affinities would change as a result. We model this as follows.

First, let be the relevance of topic *i*, where . When topic *i* has a relevance of 0.0, it should have no effect on affinities; when it is 1.0, it is fully relevant, and has the effects described in the previous sections.

Next, let

This is group *f'*s position on topic *i* given the relevance of topic *i*. Then, let

When is 1.0, the model will return the same results as before; and as decreases, every entity’s position on topic *i* will decrease with it, reducing both agreements and disagreements. When is 0.0, both agreements and disagreements on topic *i* will be 0.0, and the topic will have no effect on the results.

Or rather, it *would* have no effect on the results if it weren’t for playbox commonality, which is defined as

for

where is the playbox commonality dial and *N* is the number of topics. The intent of the playbox commonality value is to balance the explicit topics, which tend to disagreement, with an equal number of implicit topics on which there is general agreement. Decreasing topic relevance effectively decreases the number of explicit topics. For example, a belief system with ten completely irrelevant explicit topics would result in highly positive affinities based on the playbox commonality’s implicit topics. Hence, playbox commonality must be redefined as follows:

This will yield the same number as before when is 1.0 for all *i*, and will decrease proportionately as relevance decreases, thus balancing the relevant topics and not the irrelevant topics.

#### Summary

Our model of affinity with implicit causality taken into account can be stated as follows:

Let

= Playbox commonality dial, where ; the value is nominally 1.0.

= Entity commonality dial, where ; nominally 1.0 for local entities and 0.0 for non-local entities.

= The relevance of topic *i*

Then

This is the fundamental affinity equation. It cannot simply be used as is, however, because there are several pathological sets of inputs; see Section 3.3

#### Are the Properties Met?

This model meets our desired properties.

* .
* Affinities of –1.0 should be pathological. In fact, extreme inputs are required to reach either extreme, which is a good thing. In particular, the pathological affinity of –1.0 can only be reached when is zero for at least one topic; and this itself is a pathological input.
* Affinities are asymmetric. Although the agreement and disagreement metrics are symmetric, *f’*s affinities are driven by his own positions and emphases.
* The disagreement metric does not capture differences in sign; but sign still matters, because is zero when the two groups’ positions differ in sign.
* Strong disagreements do not yield indifference, that is, is not zero unless is 1.0 for the relevant topics.
* Zealots do distrust the lukewarm, provide that “zealot” is defined as a group that has a high and a low .
* The lukewarm do admire the zealots. Affinity will be positive if signs are the same and is high on the topics for which group *f* is lukewarm and *g* is zealous.
* The ambivalent distrust the zealous, because is included in the term.
* is continuous for small changes in and , even (once the special cases are handled) as goes to 0.0.
* The value of is reasonable even when the number of topics is 1.

### Computing Affinity

The formula for given in section 3.2.5.4 is substantially what we want, and behaves nicely for non-pathological inputs. Preventing division by zero and providing continuous outputs in the presence of pathological inputs requires special handling, as shown in this section.[[5]](#footnote-5) All of what follows assumes the definitions made in Sections 3.1 and 3.2.2.

In general, special cases occur when is 0 for one or more topics, that is, when group *f’*s emphasis is wholly on disagreement. Following our original terminology, we refer to this as the “zero-tolerance” case: group *f* will not tolerate even the slightest disagreement on such a topic.

#### Definitions

We make the following additional definitions:

*I* = {all *i*}, the set of all topics shared by groups *f* and *g*.

*J* = {}, the set of all topics for which group *f* has zero tolerance for disagreement.

*K* = {}, the subset of *J* for which entities *f* and *g* do not completely agree.

*L* = {}, the set of all topics for which group *f* does tolerate some disagreement. Note that .

#### The Cases

**Case A:**

In this case,

Group *f* has no zero-tolerance topics, there is no commonality between *f* and *g*, and for all *i*. In short, nobody cares about anything, so the affinity between *f* and *g* is zero.

**Case B**:

In this case,

Group *f* has at least one zero-tolerance topic, but *f* and *g* agree completely on all such topics; there is no commonality between *f* and *g*; *f’*s zeal is zero on all topics; and because *g* agrees with *f* on all of the topics in *J*, *g’*s zeal is also zero on them. In short, *f* has at least one “zero-tolerance” topic, and while it agrees completely with *g* on all such topics, it also doesn’t care about any of them.

**Case C:**

In this case,

This is the pathological “zero-tolerance” case. Group *f* tolerates no disagreement on at least one topic about which it and *g* disagree.

**Case D:**

In this case,

Group *f* has at least one zero-tolerance topic, but the two groups agree perfectly on all such; and the other terms are non-trivial.

**Case E:**

This is the nominal case; and in this case we can use the equation we derived in Section 5:

Note, however, that when the formula shown in Case D simplifies to this one. Consequently, the code can use the Case D formula for both cases D and E.

### Congruence

Information operations campaigns (and advertising in general) appeal to the civilian population by appealing to their values, that is, to their beliefs. We say that messages of this kind rely on a *semantic hook* to catch their listeners. Such a semantic hook will consist of positions on a small number of topics, much smaller than the full set used to compute affinity. (Indeed, semantic hooks can include positions on topics that are not important enough to be used when computing affinity.)

By limiting our affinity equation to only those topics contained in the semantic hook, we can compute the *congruence* of the semantic hook with a group's belief system. Denoted , where , congruence is the affinity of the group for the positions expressed by the hook. Note that unlike standard affinity, *congruence* is not bidirectional:

* The congruence of the hook with the group is the group's affinity for the hook's positions.
* The hook not a group or an actor; it has no affinities of its own.

When semantic hooks are used to compute congruence, it is common that the belief system will include a number of topics that are only used for this purpose, independent of the topic relevance. Thus, every topic has an *affinity flag*, that indicates whether or not it should be used when computing group-to-group affinities.

#### Computing Congruence

Congruence is computed in the same way as affinity, with these differences:

* The group is group *f*.
* The hook stands in for group *g*.
* The algorithm doesn't depend on group *g*'s emphasis on agreement/disagreement, so the hook doesn't contain one.
* The algorithm looks only at the topics contained in the hook.
* The hook's entity commonality, , can be set according to the perceived sender of the message containing the hook, or 1.0 by default.

## The URAM Curve Manager

The section describes the URAM curve manager, and its notion of attitude curves. The URAM curve manager underlies URAM proper.

Version 3 of Athena contained two distinct kinds of attitude curves; and these kinds differed in their dynamic characteristics: satisfaction and cooperation curves on the one hand, and vertical relationship curves on the other. GRAM handled the one, and the Athena handled the other *ad hoc*. The URAM curve manager provides a framework that supports both kinds of curve, and offers many additional possibilities.

### The Attitude Equations

This section describes the mathematics behind URAM's notion of attitude curves, as implemented by ucurve(n), the URAM curve manager. It also explains how this notion grew beyond that of GRAM.

#### Classic Satisfaction and Cooperation Curves

The basic equation in classic GRAM is the following:

where

= The level of the attitude at time *t*.

= The current change in the attitude due to level and slope effects (i.e., rule set inputs)

That is, at each time step we compute the change in attitude due to level and slope effects, , and add it to the previous time step’s attitude to get the current attitude.

Note that in this model all attitude changes at this time step persist indefinitely: the value at the next time step is the value at this time step plus any deltas. This persistent character is a big problem for longer time scales; even very small slope effects can drive an attitude curve to its minimum or maximum value over the course of a few months.

Classic GRAM also supports magic attitude adjustments, which are essentially changes made directly to between time advances. Because they occur between time advances, they are not included in the equation shown above.

#### Vertical Relationship Curves

In Athena v3, vertical relationships are handled by the application rather than by GRAM, and the fundamental equations are different:

where

= The vertical relationship at time *t*

= The baseline vertical relationship at time *t*

= Transient deltas to the vertical relationship at time *t*

= The time at which control of the relevant neighborhood last shifted.

That is to say, at each time step the vertical relationship is the baseline value plus the current deltas, which are completely transient. The baseline only changes in response to particular events in the simulation, e.g., when a different actor gains control of a neighborhood.

Thus, we can remove the reference to by rewriting these equations as follows:

where is the sum of any adjustments made to the baseline at time *t*—and the baseline is only adjusted when control of the neighborhood shifts.

#### The Unified Equations

We can represent both of the classic patterns with a single set of equations. This section and those following build up the equations in several steps. First,

where

= The current value of the attitude at time *t*

= The baseline value of the attitude at time *t*

= The current deltas, due to input effects, at time *t* (see Section 4.4)

= The current level multiplier

= The baseline level multiplier

If we set to 1.0 and to 0.0, we get the GRAM equations; if we set to 0.0 and to 1.0 we get the Athena vertical relationship equations. Now, let us add some constraints on and :

.0

.0

The equation can now be interpreted as an exponential smoothing equation, with as the smoothing coefficient: the new baseline is a moving average of the current value with past history, which is represented by the old baseline. Thus, we can see that in GRAM we throw away past history when computing the baseline; only the current level matters. With vertical relationships we only look at past history when computing the baseline. But we can easily pick values of in between 0.0 and 1.0 and thus keep varying amounts of the history. And this is exactly what we want to do.

#### Regression to a Natural Level

In GRAM we can use trends and thresholds to make a curve regress to some desired natural level. The mechanism is clumsy and difficult to use. We can add a similar though much simpler capability to our unified equations, as follows:

where

= The natural level of the attitude at time *t*

= The natural level multiplier

and

Just as pulls the baseline toward the current level, so pulls the baseline toward the natural level. If both and are non-zero, with larger than , then the baseline will move towards when is large, but towards when is small.

The value of can be set at time 0 and left alone; or it can be recomputed at each time step according to some external model. For example, the natural level of a group’s SFT satisfaction is naturally some function of the group’s security. As the group’s security increases and decreases, so should increase and decrease.

If an attitude type has no natural level, then can be set to 0.0 and the value of is irrelevant. We suggest that be set to 0.0 in such cases.

#### Persistent and Transient Deltas

Because the is added to the current level,, rather than to the baseline, it is said to be transient—it only persists to the extent that the factor rolls into . We can also support persistent changes, i.e., changes made directly to the baseline. The new equations look like this:

where

= Persistent deltas due to input effects

= Nominal baseline at time *t*, before persistent deltas are applied.

We introduce the term because of scaling; persistent effects will be scaled with respect to , while transient effects will be scaled with respect to . See Section 4.4 for more information.

#### Clamping

The and terms can be arbitrarily large, even with scaling, leading to results that are out-of-bounds for the attitude. Thus, we need to clamp the results within the [*min*, *max*] range for the attitude typewhen computing and . Thus, the final statement of the equations is the following:

where the clamp(*x*) function returns:

* *min* if *x* is less than *min*,
* *max* if *x* is greater than *max*,
* and *x* otherwise.

#### The Complete Equations

Putting it all together, we have the following:

where

= The current value of the attitude at time *t*

= The baseline value of the attitude at time *t*

= The nominal baseline at time *t*, before persistent deltas are applied.

= The natural level of the attitude at time *t*

= Transient deltas due to input effects at time *t*

= Persistent deltas due to input effects at time *t*

= The current level multiplier

= The baseline level multiplier

= The natural level multiplier

and

### Attitude Types

In principle, an attitude curve is defined by eight parameters:

*min* = The minimum curve value

*max* = The maximum curve value

*α* = The current level multiplier

*β* = The baseline multiplier

*γ* = The natural level multiplier

= The current level of the attitude at time 0

= The baseline level of the attitude at time 0

= The natural level of the attitude at time 0

which are subject to the following constraints:

Rather than defining all eight of these parameters for each attitude curve, we find it convenient to group the existing attitude curves into types (e.g., satisfaction with the four concerns, horizontal relationships, vertical relationships, and cooperation levels). In this scheme, the type defines the *min*, *max*, *α*, *β*, and *γ* parameters, and the individual curve has its own , , and parameters.

The URAM Curve Manager does not itself define any specific curve types; that is left to the client (i.e., URAM proper).

### Baseline Adjustments

A baseline adjustment[[6]](#footnote-6) is an absolute, unscaled step change to the baseline of the curve caused by some attitude driver. Adjustments are applied between time advances, and affect the value of directly. The adjustment delta is ascribed to the driver at the next time advance (See Section 4.6).

It is unusual to have more than one adjustment on a curve in a single time step.

### Transient Effects

A transient effect represents how a particular attitude driver affects an attitude during this time step, i.e., it is a contribution to . For example, my quality-of-life might be lower than usual right now because the power is out. My QOL satisfaction might change by -5.0 points, and this effect will remain so long as the power remains off. When the power comes back on the effect will disappear. (Whether or not the baseline QOL value will change as a result of the power outage depends on the value of used with QOL curves.) This is a transient effect.

Unlike GRAM slope effects, which remained in GRAM and continued to have an effect time-step-by-time-step until they were explicitly terminated, URAM’s effects apply to a single time step and then disappear. If the attitude driver (i.e., a situation) persists across time steps and should have a transient effect in each time step, it must create a new transient effect in URAM at each time step.

Transient effects are much more complicated than adjustments, as they inherit the cause-and-scaling model from GRAM. On the other hand, they are simpler than GRAM’s level and slope effects. Each effect is defined by the following attributes:

* The magnitude, expressed as some number of nominal percentage points of change.
* The cause, expressed as an integer ID.[[7]](#footnote-7)

We will discuss each of these in turn.

#### Scaling of Contributions

The actual contribution of a transient effect to an attitude curve should show the effects of diminishing returns (technically, *diminishing marginal utility*) as the extreme values are approached. Specifically:

* Positive contributions should have a stronger effect when is near *min* and a weaker effect when is near *max*.
* Negative contributions should have a stronger effect when is near *max* and a weaker effect when is near *min*.
* Ideally, should stay within the range without being artificially clamped.

To achieve this, we scale each nominal contribution to given the current value of , producing the actual contribution. The following function has the desired properties provided that the total unscaled contributions at each time step are less than 100.0 in absolute terms. (If they are greater, the value of will be clamped.)

First, the nominal magnitude *M* of a transient effect is a number representing a percentage change in the attitude relative to baseline *B*. The function computes the actual magnitude , which is the delta that produces the percentage change in *B*. The *B*, *min*, and *max* parameters depend on the attitude curve for which scaling is being computed and can be known from context; hence, although the function would more properly be written “scale(*M, B, min, max*)” we will usually write it “scale(*M*)”.

For example, suppose that *M* is 10.0. This represents a 10% change from the baseline to *max*. The following table shows the actual contribution of a nominal 10.0 point change for a curve with bounds (-100.0, +100.0) and several different baselines.

|  |  |  |
| --- | --- | --- |
|  | *M* |  |
| -100.0 | 10.0 | 20.0 |
| -50.0 | 10.0 | 15.0 |
| 0.0 | 10.0 | 10.0 |
| +50.0 | 10.0 | 5.0 |
| +100.0 | 10.0 | 0.0 |

#### Causes and Scaling

Section 4.4.1 shows how to compute the scaled contribution to of each transient effect during a given time step. There is one more piece to the puzzle.

We could simply compute the contribution of the transient effects during time step *t* as follows:

where

= The nominal magnitude of the *i*th transient effect

This, however, presumes that the transient effects at time *t* are all independent of one another, and that each should always contribute its full scaled magnitude. This is not necessarily the case. Transient effects are the result of independent drivers that affect the local civilian population and hence affect their attitudes. But even if the drivers are independent, the effects need not be.

People's capacity to respond to events and situations, their ability to feel horror and dismay on the one hand or joy and exultation on the other, can be saturated on a number of axes. Once their capacity is saturated due to drivers of a particular kind, further events of that kind occurring shortly thereafter are unlikely to have much additional effect. Consider, for example, a neighborhood that is experiencing a serious epidemic. It's unlikely that a second epidemic afflicting the neighborhood—or the indirect effects of an epidemic in the neighborhood next door—will change the results much. The first epidemic does whatever damage will be done.

The URAM Curve Manager handles this through the notion of *causes*. Each transient effect is assigned a *cause*. Effects due to similar drivers—e.g., epidemics—will have identical causes.

When effects on curve share a single cause, their total contribution is the contribution of the largest effect. More precisely, for each cause *k* let be the set of effects *i* that have cause *k* and for which ; similarly, let be the set of effects *i* that have cause *k* and for which *.* The nominal contribution of the effects with cause *k* is then

We can then say that

We would then like to compute the actual contribution of each effect *i* to this final result. The scaled contribution of each level effect *i* with cause *k* is shared with the other effects with cause *k* that are active in that time step. The following equation allocates the total scaled contribution back to each of the constituent effects on a *pro rata* basis, resulting in the effect's actual contribution during time step *t*:

Accumulating the actual contributions to date is useful because it allows us to see precisely how the effect has changed —and ultimately, how a given driver has changed attitudes in general.

### Persistent Effects

Some attitude drivers, e.g., power outages are essentially transient. While the power is out, it is a problem; when the power comes back on, the problem goes away. Other attitude drivers, however, cause a one-time, persistent change in an attitude. When control of a neighborhood shifts from one actor to another, for example, there is a persistent one-time change in satisfaction.

Persistent effects are similar to transient effects, and their contributions are computed in essentially the way. The distinctions are as follows:

* Persistent effects contribute to rather than .
* Persistent effects are scaled with respect to rather than with respect to .

### Historical Data

Every adjustment and effect is generated by some attitude driver known to the client. In order to understand causality, we need to relate drivers to their contributions. Consequently, at each time *t* we will save the total contribution of driver *d* to each curve for later retrieval. For baseline adjustments, the contribution is simply the value of the adjustment; for persistent and transient effects, it is as computed in Section 4.4.2.

### Applying Adjustments and Effects

When time is advanced, all pending adjustments and effects must be applied and the curve’s and values computed. The algorithm is as follows:

Update based on external models, if need be.

Save the contributions of baseline adjustments by driver.[[8]](#footnote-8)

Compute , along with the resulting positive and negative scaling factors.

Compute given any pending persistent effects.

Compute , along with the resulting positive and negative scaling factors.

Compute given any pending transient effects.

Compute .

Save the contributions of all persistent and transient effects by driver.

#### Applying Transient Effects Only

As a practical matter the initial input to URAM will include , the initial baseline level, but not , the initial current level, because depends on transient effects, which in turn depend on simulated attitude drivers. At *t*=0, then, we will need to apply transient effects based on the initial state of the simulation. At the same time, we are given ; if we apply the algorithm shown just above, we will recompute , which we do not want to do. Thus, at *t*=0 we will compute by applying transient effects only, using the following algorithm:

Save the contributions of baseline adjustments by driver.[[9]](#footnote-9)

Compute the positive and negative scaling factors for .

Compute given any pending transient effects.

Compute .

Save the contributions of all transient effects by driver.

### Examples

This section shows graphically the effect of different settings of α, β, and γ on transient effects. Consider a satisfaction Quality-of-Life (QOL) curve, and a driver that causes a −10.0 nominal change each week for four weeks. With our classic model (, this results in the following graph (assuming that QOL began at 0.0):

The actual and baseline levels drop by 10.0 points each week, leaving satisfaction at −40.0 after four days. The driver ends, and in the absence of other drivers the curve simply sits there at −40.0. If we change to 0.9, (that is, ) we get this instead:

Satisfaction drops immediately, and stays approximately 10.0 points worse than before for all four weeks. After that, the effect ends, and things are immediately about 10.0 points better—but not completely. The negative transient effect has dragged the baseline down by about 4.0 points over the four weeks, and and so the group is less satisfied with QOL than before the driver occurred. Note especially that while the classic model ran away very quickly, the new model does not.

The above graphs presume that the curve has no natural level, i.e., γ is 0.0. Assume that the curve has a natural level of , and set to 0.8 and to 0.1, leaving at 0.1. The resulting curve looks almost identical to the previous…but the curve slowly trends back toward 0.0:

The speed of the regression depends on the distance between and *C*.

## Unified Regional Attitude Model

The Unified Regional Attitude Model (URAM) is a population dynamics model of the attitudes and behavior of groups within neighborhoods within the playbox. URAM tracks changes in attitudes over time. Changes are driven by events and situations modeled within the client simulation (e.g., civilian casualties, presence of force units in a neighborhood, and so forth). The client simulation uses algorithms and rule sets to analyze these *drivers* and provide attitude inputs to URAM.

The effects of an attitude driver are not necessarily limited to the neighborhood and group that are directly affected by the driver—for certain kinds of attitude there may be second order effects on other groups in the neighborhood, and on groups in other neighborhoods. These *indirect effects* generally weaken with distance.

As simulation time progresses, URAM tracks the contribution of each driver to each attitude curve, thus enabling the significant drivers to be determined after the fact.

At present, URAM supports four different types of attitude curve: the *cooperation* of a civilian group with a force group, the *satisfaction* of a civilian group with respect to various *concerns*, the *horizontal relationship* of one group with another, and the *vertical* relationship of a group with an actor.

This section details the nature of attitude levels and curves, the kinds of inputs that can affect each, and how the results are computed. Then, it describes the specifics of the different types of attitude curve, along with any type-specific outputs.

URAM is a generalization, extension and revision of the Generalized Regional Analysis Model (GRAM) developer for use by the Joint Non-kinetic Effects Model (JNEM) and by the Athena Stability and Recovery Operations simulation. GRAM was a generalization and extension of JRAM, also developed for JNEM, which was in turn based on an earlier model called the Regional Analysis Model, or RAM. RAM was developed for the National Simulation Center by the Texas A&M University’s Department of Political Science, working with the George Bush School of Government and Public Service and the Texas Center for Applied Technology (both also at Texas A&M). RAM was part of the Spectrum Simulation to model biases, alliances, rivalries, and other aspects of inter-group relationships.

### The URAM Curve Manager

### Attitude Curves

A group's satisfaction and cooperation levels are collectively referred to as the group's *attitudes*. Attitudes will change over time, depending on what happens to the group. Events and situations that affect a group's attitudes are called *attitude drivers*, or simply *drivers*. As an attitude changes over time, it traces out an *attitude curve,* ; the value of the attitude at time 0 is denoted . The chosen unit of time is irrelevant to the model, but is usually decimal days. The value of may range from to (–100.0 to +100.0 for satisfaction curves, and 0.0 to 100.0 for cooperation curves).

More specifically, the satisfaction for group *g* with respect to concern *c* at time *t* is denoted , and the cooperation for civilian group *f* with force group *g* at time *t* is denoted . The *initial satisfaction* is and the *initial cooperation* is .

Any attitude curve is recomputed at a series of major time steps (tocks) as follows:

For simplicity in notation during the following discussion, we will use to denote the time of the current tock and to denote the time of the previous tock. The interval is typically constant for all pair of tocks, but in principle the interval could vary from tock to tock. The “contributions” at each tock are due to attitude drivers and are of two kinds:

* The contribution of level effects
* The contribution of slope effects

The client simulation’s rule sets analyze current drivers, producing level inputs and slope inputs on particular attitude curves. GRAM translates these inputs into level effects and slope effects as described in Section 4.5; these effects contribute to the attitude curves as described in Sections 4.1.1 and 4.1.2 respectively.

#### Level Effects

GRAM inputs can create *level effects* on attitude curves. A level effect is a nominal change of a specified magnitude which takes place over a specified period of time. The rate at which the effect’s magnitude, or *limit*, is realized is defined by a *realization curve*. This section explains how to compute the nominal contribution of a particular level effect to an attitude curve during some time step.

##### Level Effects Defined

A level effect can be thought of as a tuple of the following elements:

The indices of the affected attitude curve (*gc* for satisfaction curves, *fg* for cooperation curves)

* *d*, the ID of the driver that resulted in this affect.
* *k*, an indicator of the effect’s cause; see Section 4.1.5.
* *limit*, the nominal magnitude of the change
* *days*, the time interval in days over which the effect is realized
* *ts*, the effect’s start time
* *te*, the effect’s end time.
* , a parameter which controls the shape of the realization curve.

When working with a set of level effects, these parameters can be subscripted with the effect index *i*, e.g. is the *limit* of the *i*th effect.

The realization curve for a level effect is defined by the following function :

This exponential curve approaches but never actually reaches the *limit*. Consequently, is chosen that the curve is just from *limit* at time *te*:

denotes this function for a specific level effect *i*. The nominal contribution of level effect *i* at time step is therefore

Note that those level effects with or are guaranteed to contribute a value of 0 to the curve during the time step—they have either run their course before the interval starts, or have not begun to have an effect when the interval ends. For such effects,

This nominal contribution is used to compute the actual contribution of effect *i* during the time step. In addition, as the simulation runs from time step to time step we accumulate the nominal contribution to date for each level effect *i*:

Accumulating the nominal contribution to date for a level effect is useful because it allows us to watch the progress of the level effect in terms of the original inputs as the model runs forward in time.

##### Effect of Epsilon on Level Effects

GRAM uses an value[[10]](#footnote-10), nominally equal to 0.01, that affects level effects in two ways:

* As described in Section 4.1.1.1, is used to calibrate the exponential curve so that it reaches of its *limit* at its end time, *te*.
* When scheduling level effects the requested realization time in *days* is ignored for effects whose . Instead, *te* is set to *ts* and *days* is set to 0, so that the effect makes its entire contribution at time step containing *ts*.

#### Slope Effects

GRAM inputs can create *slope effects*. A slope effect is an attitude change with a specified nominal slope (change/day). The effect will cause the attitude to change at that same nominal rate until the slope effect is terminated or reaches a threshold. This section explains how to compute the nominal contribution of a particular slope effect during some time step.

##### Slope Effects Defined

A slope effect can be thought of us a tuple of the following elements:

The indices of the affected attitude curve (*gc* for satisfaction curves, *fg* for cooperation curves).

* *d*, the ID of the driver that resulted in this effect
* *k*, an indicator of the effect's cause; see Section 4.1.5
* *slope*, the nominal change per day
* *ts*, the effect's start time in ticks
* *te*, the effect's end time in ticks

When working with a set of slope effects, these parameters can be subscripted with the effect index *i*, e.g., is the *slope* of the *i*th effect.

It would seem that the nominal contribution of a slope effect *i* for time step is simply the *slope* times the duration of the time step:

However, the effect might not apply for the full time interval; indeed it might not apply for any of the time interval. There are the following cases:

* , in which case the effect hasn't yet started to contribute to satisfaction.
* , in which case the effect is no longer contributing to satisfaction.
* and , in which case the effect is contributing for some or all of the interval.

Consequently, we define

As the simulation runs from time step to time step we accumulate the nominal contribution to date for each slope effect, just as we did for level effects:

However, we must also consider *slope chains*.

##### Situations and Slope Chains

A slope chain is a sequence of slope effects related to a single driver, usually a *situation[[11]](#footnote-11)*, all of which target the same attitude curve. Chains are produced when a situation evolves over time, producing a sequence of slopes. The essential thing about effects in a slope chain is that they may not overlap in time, precisely because the chain really represents a single effect that happens to fluctuate over time.[[12]](#footnote-12) (Section 4.5 describes the genesis of slope chains in detail).

The following table represents a slope chain for some particular situation *d*. Note that all effects in the chain have the same *d*, curve indices, and *k*; these values are therefore omitted from the table:

|  |  |  |
| --- | --- | --- |
| TS | TE | SLOPE |
| 7 | 24 | 5.2 |
| 24 | 39 | 0 |
| 39 | 108 | 2.5 |
| 108 |  | 7.1 |

The situation begins at tick 7, and the slope is 5.2. At tick 24 the situation becomes inactive, and the slope drops to 0. At tick 39 the situation becomes active again, with a slope of 2.5. At tick 108 things heat up and the slope rises to 7.1. Note that the final effect in the chain has no end time; slope chains are terminated by setting the slope to 0 in the final link in the chain.

The presence of slope chains affects the model in two ways. First, care must be taken when scheduling a new effect to update any exist chain. If the situation above were to change again at time 134, for example, the existing chain would need to be extended with the new slope.

Second, it is possible that several links in a chain will contribute to satisfaction during a single time step, e.g., if the slope changes several times during the time step. Since the links really represent a single fluctuating effect, the total nominal contribution of the links must be considered when computing the actual contribution of the chain.

Extending the equations described in the previous sections to account for slope chains would be a tedious exercise in notation. To summarize, then, the implementation must account for the following:

* A new link in a slope chain must terminate any previous link in that chain.
* The nominal contribution must be computed for the chain as a whole.
* If two or more links in a chain are active during a single time step, they must be treated as a single effect with respect to the computation of the actual contribution to the attitude curve.

##### Effects of Epsilon on Slope Effects

The same used in the scheduling and assessment of level effects is applied to slope effects in a different way. If, when a slope effect is being scheduled, its , it will treated as though its . This prevents the computation of insignificant slope effects (and particularly of insignificant indirect effects) from affecting performance.

#### Ascending and Descending Thresholds

Every level and slope effect has, in addition to the elements shown above, an *ascending threshold* and a *descending threshold*, which are used to filter out effects when the nominal contribution is computed. These thresholds are denoted *athresh* and *dthresh*. The notion is that the given effect cannot increase the underlying curve *A* if , and cannot decrease the underlying curve *A* if . Thus, a given satisfaction slope effect might have a slope of -5.0 and a *dthresh* of -20: the curve will lose 5 nominal points per day, but only up to a threshold of -20 satisfaction points. The effect is reasonably sharp, but cannot make the group more than mildly annoyed. On the other hand, so long as the effect is in place it may be difficult to improve the group's mood much above -20.

The handling of thresholds is straightforward: effects for which the underlying curve exceeds the relevant threshold are treated as though their nominal contribution were zero.

The thresholds are set when the effect is scheduled.

A judicious use of thresholds can greatly enrich the notion of the trend; see Section 4.3.4.

#### Scaling of Contributions

The actual contribution to any attitude curve should show the effects of diminishing returns (technically, *diminishing marginal utility*) as the extreme values are approached. Specifically:

* Positive contributions should have a stronger effect when is near and a weaker effect when is near .
* Negative contributions should have a stronger effect when is near and a weaker effect when is near .
* should stay within the range to without being artificially clamped.

To achieve this, each non-zero *nominal contribution* to is scaled given the value of , producing the *actual contribution*. The following scheme has the desired properties, provided that the total actual nominal contributions at each time step are less than .

First, for each nominal contribution *ncontrib* to satisfaction curve , let

With this formula, a nominal contribution of 10 points will cause the satisfaction level to move 10% of the distance from its current value toward the upper limit, +100, no matter what that current value actually is. Similarly, a nominal contribution of –10 points will cause the satisfaction level to move 10% of the distance from its current value toward the lower limit of –100. Consequently, nominal contributions can be thought of either as points *or* as percentage changes in the difference between the current value and the extreme.

Similarly, for each nominal contribution *ncontrib* to cooperation curve , let

In the sections that follow, the notation "" indicates that *x* has been scaled in this way.

#### Causes and Scaling

The discussions in Sections 4.1.1.1 and 4.1.2.1 show how to compute the nominal contribution of each level and slope effect during a given time step. Section 4.1.4 shows how the contributions can be scaled so that the attitude level does not get clamped at its maximum or minimum value. There is one more piece to the puzzle.

We could simply compute the actual contribution during the time step from to as follows:

This, however, presumes that the collection of level and slope effects that are active at a given time are all independent of one another, and that each should always contribute its full scaled magnitude. This is not necessarily the case. Level and slope effects are the result of independent drivers which affect the local civilian population and hence affect their attitudes. But even if the drivers are independent, the effects need not be.

People's capacity to respond to events and situations, their ability to feel horror and dismay on the one hand or joy and exultation on the other, can be saturated on a number of axes. Once their capacity is saturated due to drivers of a particular kind, further events of that kind occurring shortly thereafter are unlikely to have much additional effect. Consider, for example, a neighborhood which is experiencing a serious epidemic. It's unlikely that a second epidemic afflicting the neighborhood at the same time will change the results much.

GRAM handles this through the notion of *causes*. Each input to GRAM can be assigned a *cause*. Inputs due to similar drivers—e.g., bombings—will have identical causes. All effects stemming from a single input will share that input's cause.

When contributions to a single curve share a single cause, their total contribution is the contribution of the largest effect. More precisely, for each cause *k* let be the set of effects *i* that have cause *k* and for which ; similarly, let be the set of effects *i* that have cause *k* and for which *.* The nominal contribution of the effects with cause *k* is then

If we treat GRAM inputs for which no cause is specified as having a unique cause *k*, then the attitude level at time step is

We would then like to compute the actual contribution of each effect *i* to this final result. The scaled contribution of each level effect *i* with cause *k* is shared with the other effects with cause *k* that are active in that time step. The following equation allocates the total scaled contribution back to each of the constituent effects on a *pro rata* basis, resulting in the effect's *actual contribution to date*:

Accumulating the actual contributions to date is useful because it allows us to see precisely how the effect has changed —and ultimately, how a given driver has changed attitudes in general.

### Neighborhoods and Groups

Having discussed attitude curves in general, it's now time to discuss satisfaction and cooperation curves in specific. But first, we must discuss neighborhoods and groups.

GRAM models attitudes in a geographical region called the *playbox*. The playbox is divided into areas, which are called *neighborhoods*. Similarly, the civilian population of the playbox is divided into groups. Each group *g* resides in a particular neighborhood *n.*

GRAM tracks satisfaction for each civilian group, and also tracks cooperation for each civilian group with each force group.

### Satisfaction

GRAM tracks the satisfaction of civilian groups with respect to each of the groups' concerns. Summary statistics are computed for each group and each neighborhood.

#### Satisfaction Levels

The degree to which a group is satisfied with its condition with respect to some concern is described by a satisfaction value, sometimes called a *satisfaction level*. A satisfaction value is a decimal number *S*, where . A value of +100 denotes perfect satisfaction, and a value of -100.0 denotes utter dissatisfaction. The following rating scale is frequently used:[[13]](#footnote-13)

|  |  |  |  |
| --- | --- | --- | --- |
| SYMBOL | MEANING | MIDPOINT | RANGE |
| VS | Very Satisfied | 80.0 |  |
| S | Satisfied | 40.0 |  |
| A | Ambivalent | 0.0 |  |
| D | Dissatisfied | -40.0 |  |
| VD | Very Dissatisfied | -80.0 |  |

Note that this is a relative scale. Satisfaction is measured on several axes, and different groups place different weights on different axes. Thus, satisfaction values must generally be weighted in order to be comparable. See the discussion of saliency in Section 4.3.3.

#### Concerns

A group may be satisfied or dissatisfied along several different axes, e.g., personal safety, quality of life, and so forth. In GRAM these axes are called *concerns*. GRAM itself doesn't care what the concerns are; the client simulation is free to define any concerns it chooses. However, there is a standard set of civilian concerns that has generally been used over the last several years:

**Autonomy (AUT):** Does the group feel it can maintain order and govern itself with a stable government and a viable economy?

**Safety (SFT):** Do members of the group fear for their lives, either from hostile attack or from collateral damage from force activities? This fear includes environmental concerns such as life-threatening disease, starvation, and dying of thirst.

**Culture (CUL):** Does the group feel that its culture and religion, including cultural and religious sites and artifacts, are respected or denigrated?

**Quality of Life (QOL):** QOL includes the physical plants that provide services, including water, power, public transportation, commercial markets, hospitals, etc., and those things associated with these services, such as sanitation, health, education, employment, food, clothing, and shelter.

#### Composite Satisfaction, Weights, and Saliencies

The satisfaction of group *g* with respect to concern *c* is denoted . It is frequently desirable to summarize the full matrix using a variety of weighted averages, collectively termed *composite satisfaction* values. For example, we are often interested in group *g*'s composite satisfactionover all concerns; this is called the group's *mood*, and is denoted .

We could compute such composites using a simple average, but that would neglect two important factors. First of all, a group usually places more importance on some concerns than others, and different groups often place importance on different concerns. The importance[[14]](#footnote-14) a group places on a concern is called the group's *saliency* for the concern. Saliency is represented by a number where . The following rating scale is used:

|  |  |  |
| --- | --- | --- |
| SYMBOL | MEANING | VALUE |
| CR | Crucial | 1.00 |
| VI | Very Important | 0.85 |
| I | Important | 0.70 |
| LI | Less Important | 0.55 |
| UN | Unimportant | 0.40 |
| NG | Negligible | 0.00 |

When averaging across concerns we must weight by the saliency of each. Note that this is an absolute scale.

Second, different groups are of different sizes, and some groups have more importance to the wider community than other groups. To a first approximation, the importance of a group will be proportional to its size; hence, we weight by the population of each group, .[[15]](#footnote-15) in that the size of a neighborhood group will affect its importance to the group as a whole; however, a small elite group can have a higher weight than a large underclass.

It has been shown[[16]](#footnote-16) that the following equation properly "rolls up" satisfaction across any set *A* of groups and concerns:

Given this, we can define the following useful composite satisfactions.

The mood of each group *g* (note that the population term drops out):

The mood of each neighborhood *n:*

#### Trends

A *trend* (also known as a *long-term trend*) is a systematic effect on an attitude curve. Earlier versions of GRAM explicitly defined the long-term trend as a slope effect producing a steady increase or decrease in a satisfaction curve over time. Current versions of GRAM simply allow the client simulation to define long-term trend effects on their own; the trend then becomes just another driver.

Thresholds (Section 4.1.3) make trends much more useful, because any slope effect, if applied over a long period of time, will drive an attitude curve to its minimum or maximum extreme. Thresholds limit trends to a more reasonable effect.

Trends can be even more useful when implemented in pairs. For example, regression to a mean (0.0, say) can be implemented by creating a positive slope effect with an *athresh* of 0.0 and a negative slope effect with a *dthresh* of 0.0. When the curve is negative, the first will drive it up to 0.0; when it is negative, the second will drive it down to 0.0.

See Section 4.1.2 for more information about slope effects, and Section 4.5 for more information about drivers.

### Cooperation

GRAM tracks the *cooperation* of civilian groups with force groups. Cooperation is a concept that derives from the TRADOC HUMINT methodology; it indicates the likelihood that one group *f* will provide intelligence to another group *g*. Note that cooperation is distinct from providing active aid to another group; this is sometimes called *collaboration*. GRAM does not model collaboration.[[17]](#footnote-17)

#### Cooperation Levels

The probability that a member of civilian group *f* will provide intelligence to a member of force group *g* is expressed as a number between 0 and 100 called the *cooperation level* of *f* with *g* and is denoted . Note that the information flow is always from group *f* to group *g*, i.e., from the first group to the second.

Cooperation levels are often represented symbolically, as indicated in the following table:

|  |  |  |  |
| --- | --- | --- | --- |
| SYMBOL | MEANING | VALUE | RANGE |
| AC | Always Cooperative | 100.0 |  |
| VC | Very Cooperative | 90.0 |  |
| C | Cooperative | 70.0 |  |
| MC | Marginally Cooperative | 50.0 |  |
| U | Uncooperative | 30.0 |  |
| VU | Very Uncooperative | 10.0 |  |
| NC | Never Cooperative | 0.0 |  |

#### Composite Cooperation

The average cooperation of all of the groups in neighborhood *n* with force group *g* is denoted , and is computed as follows:

We weight cooperation by the size of the population. The cooperation of group *f* with group *g* can be thought of as the probability that an arbitrary member of group *f* will give intelligence to group *g*. Thus, when averaging across groups it makes sense to weight by the number of members in each. If the population of the neighborhood is zero, then is 0.

### Drivers, Inputs, and Effects

The client simulation analyzes attitude drivers (events and situations) and produces satisfaction and cooperation inputs for GRAM. These inputs create effects across the playbox; the distribution and relative magnitudes of these effects is called the *spread* of the input. This section explains how spread is computed and each input is turned into a collection of effects.

Each GRAM input specifies a direct effect on a particular attitude curve. This direct effect is a level or slope effect as described in Sections 4.1.1 and 4.1.2. The direct effect then engenders indirect effects on other attitude curves.

Each input optionally includes an ascending threshold (*athresh*) and descending threshold (*dthresh*) as described in Section 4.1.3. If not specified, these thresholds default to the minimum and maximum of the curve's range, i.e., the default *athresh* and *dthresh* for satisfaction inputs are +100.0 and -100.0. Each effect engendered by the input inherits the input's thresholds. This, incidentally, is why both thresholds are required. An *athresh* is only binding on a positive effect—but a positive input can produce both positive and negative effects.

Indirect effects differ from the direct effect that engenders them in two ways. First, their magnitude (*limit* for level effects, *slope* for slope effects) is affected by the relationship between the group directly affected and the group indirectly affected, and by the relationship between the neighborhoods in which they reside. Second, indirect effects in other neighborhoods can be delayed by an interval that depends on the two neighborhoods.

This section explains how to determine the magnitude and delay for each indirect effect. Before we can define them, however, we must first define the proximity and effects delay between two neighborhoods.

#### Neighborhood Proximities

Whether or not a GRAM input in neighborhood *n* has indirect effects in another neighborhood *m* depends in part of the proximity of neighborhood *m* to neighborhood *n*, and on the nature of the driver. For example, combat in a neighborhood will likely concern residents in nearby neighborhoods, and might even concern residents in far away neighborhoods. Other situations, such as a sewage spill, might only concern residents of the neighborhood in which the spill occurs.

Neighborhood proximity is defined by the matrix, which defines the proximity of neighborhood *n* to neighborhood *m* from the point of view of residents of *m*. Each element of the matrix must have one of the following values:

|  |  |  |
| --- | --- | --- |
| VALUE | SYMBOL | NOTES |
| 0 | HERE | *m* = *n*; indirect effects always occur. |
| 1 | NEAR | *n* is near *m*; indirect effects are common. |
| 2 | FAR | *n* is far from *m*; indirect effects are rare. |
| 3 | REMOTE | *n* is remote from *m*; indirect effects never occur. |

Note that proximity, in this sense, is not simply a measure of miles walked or driven, but rather a perception on the part of the residents of neighborhood *m*. For example, neighborhoods A and B might be adjacent on the map, but have a natural boundary (e.g., a river) between them, such that residents of A seldom travel to B; thus, residents of A might consider B to be FAR. Neighborhood C might be farther from A than B is, but C contains a popular destination, e.g., a shopping district, or an industrial district that employs many of the residents of A. The residents of A would then consider C to be NEAR, even though it's farther away than B, which is considered to be FAR.

Also, note that need not be symmetric; it is okay if . In our example, the residents of A frequently visit C and so regard C as NEAR; but if the residents of C seldom visit A, they might regard A as FAR.

For convenience, we also define the following symbols:

Because each civilian group resides in a single neighborhood, we can reasonably talk about the proximity between a pair of civilian groups *f* and *g*, denoted , and can then go on to define , , and so forth.

#### Proximity Limits

Because a single GRAM input can produce a vast quantity of indirect effects, performance may become an issue in practice. GRAM implements the notion of the *proximity limit[[18]](#footnote-18)* as a means to cope with GRAM performance issues during training exercises. The proximity limit may be set as indicated in the following table:

|  |  |
| --- | --- |
| LIMIT | CONSEQUENCES |
| far | An input in neighborhood *n* may have indirect effects in *n*, in neighborhoods near *n*, and in neighborhoods far from *n*. |
| near | An input in neighborhood *n* may have indirect effects in *n* and neighborhoods near *n*. If the proximity limit is changed to “near”, existing indirect effects in far neighborhoods will be terminated. |
| here | An input in neighborhood *n* will have indirect effects only in *n*. If the proximity limit is changed to “here”, existing indirect effects in near and far neighborhoods will be terminated. |
| none | No indirect effects will be scheduled. If the proximity limit is changed to “none”, all existing indirect effects will be terminated. |

#### Neighborhood Effects Delay

When an event occurs in neighborhood *n*, the response to that event in another neighborhood *m* may be delayed: news takes time to spread. This delay is probably correlated with the distance between the two neighborhoods, but as with proximity geographic distance doesn't tell the whole story. Given cell phones and the Internet, communications between any two points can be nearly instantaneous, making distance moot; and yet, just because news *can* travel instantly doesn't mean that it does. Thus we define as the time delay in decimal days for an input in neighborhood *n* to have an indirect effect in neighborhood *m*. Note that forall *n;* there is no delay within neighborhood *n* itself.

As with proximity, we define as the delay between the neighborhoods in which civilian groups *f* and *g* reside.

#### Satisfaction Influence

A civilian group *g* is said to influence another civilian group *f* to the extent that direct effects on group *g* have indirect effects on group *f*. Influence depends on the proximity between the two groups, and on the relationship between them.

The relationship between the groups, , is a number from from -1.0 to +1.0, where +1.0 indicates that *f* regards *g* as a perfect friend and -1.0 indicates that *f* regards *g* as a perfect enemy. The relationship between a group and itself is usually +1.0; the relationships between other groups typically range from -0.6 to +0.6. Note that if the relationship is 0.0, then group *g* will have no indirect effects at all on group *f*. Also, note that relationships need not be symmetric; need not equal . It is up the client simulation to specify the relationships; either as input data or via a model like MAM (Section 3).

The magnitude of *g*'s influence on *f* is a multiplicative factor denoted and defined as follows:

Given a direct effect on group *g* with magnitude , then the maximum indirect effect (in absolute terms) on some other group *f* is . This ensures that the indirect effects are no bigger in absolute terms than direct effects, and they will usually be smaller.

Indirect effects are further constrained by the near and far factors associated with the satisfaction input; see Section 4.5.6.

#### Cooperation Influence

*Cooperation influence* is more complicated than satisfaction influence because each cooperation effect involves two groups rather than one, a civilian group and a force group. In previous versions of GRAM, a direct effect on the cooperation of civilian group *f* with force group *g* in neighborhood *n* could affect group *f'*s cooperation with every force group in every non-remote neighborhood, according to the relationship between force group *g* and the other force groups.

In the previous version of GRAM, each civilian group could reside in multiple neighborhoods, creating what were called *neighborhood groups*; two neighborhood groups belonging to the same top-level group would have a relationship *R* of 1.0 with each other. In this version, where each civilian group resides in a single neighborhood, groups that would have been neighborhood groups are now simply modeled as distinct groups with a strong relationship. In order to get the same pattern of indirect cooperation effects, then, we must have indirect effects on other civilian groups with strong relationships.

This results in a two-step process for determining cooperation influence: first we determine the set of affected civilian groups, and then we determine the set of affected force groups.

A civilian group *e* can be affected by a direct cooperation effect on civilian group *f* if the proximity between groups *e* and *f* is not remote and group *e* has a strong enough relationship with group *f*, or, in other words, when , where *CRL* is the cooperation relationship limit.[[19]](#footnote-19) Thus, a force group's treatment of *f* affects the attitudes of *f'*s close friends toward that same force group.

Then, the cooperation influence of force group *g* on force group *h* is simply the relationship between the two groups, . The indirect effects apply to all civilian groups *e* that meet the above requirement and all force groups *h*.

Thus, if *g* does something to antagonize *f*, thus decreasing *f'*s cooperation with *g*, then *f'*s cooperation also decreases with friends of *g*, and increases with enemies of *g*.[[20]](#footnote-20) The same applies for *f'*s friends *e*.

#### Here, Near, and Far Factors

The influence factors determine the maximum indirect effect a direct effect may have on each neighborhood and group. However, different drivers differ in scope. For example, accumulation of garbage or raw sewage in the streets of a neighborhood is likely of concern only to the residents of that neighborhood, whereas combat in a neighborhood is almost certainly of concern to residents of near neighborhoods, and possibly of concern to those in far neighborhoods as well. Typically we assume that indirect effects are strongest HERE, decrease in NEAR neighborhoods, and decrease even more in FAR neighborhoods. This is controlled by three parameters associated with each satisfaction and cooperation input: the *here* factor, denoted *s*, the *near factor*, denoted *p*, and the *far factor*, denoted *q*. We require that

The values of *s*, *p,* and *q* can vary from input to input, even for a single driver; however, we usually define *s*, *p* and *q* to be the same for all inputs for each kind of driver. Moreover, *s* is usually 1.0.

#### Computing Spread

Given the terms defined in the preceding sections, we can now define the direct and indirect effects resulting from an input to GRAM. First, the direct effect is simply a level or slope effect as defined in Section 4.1. It will have a magnitude, which is called the *limit* for level effects and the *slope* for slope effects; here, we'll call it simply *M*.

The indirect effects *j* on civilian group *f* of a direct satisfaction effect *i* to civilian group *g* will have magnitude

In other words, the direct magnitude is adjusted by the influence factor, and by *s*, *p,* and *q* as appropriate.

All indirect effects are delayed by ; thus, if the direct effect has start time and end time , the indirect effects will have start and end time

Similarly, the indirect effects *j* on civilian group *e* and force group *h* of a direct cooperation effect *i* on civilian group *f* with force group *g* will have magnitude

The effects will be delayed in the same way as satisfaction effects.

Note that when scheduling slope effects, the bookkeeping associated with slope chains must also be done; see Section 4.1.2.2.

### Dynamic Civilian Groups

In versions of GRAM prior to Mars 1.39, civilian groups resided in neighborhoods and did not move. In the real world, and especially in war zones, mass migration is common. Due to war, catastrophes, or simply a nomadic lifestyle, populations move and shift, and GRAM needs to allow them to take their attitudes with them. This section describes a set of operations added to GRAM in support of scenarios involving population movement.

#### Use Cases

This section describes the kinds of population movement we envision, based on discussions with NSC, BCTP, and TRISA personnel over the last few years.

* Civilians flee a neighborhood in fear for their lives, and regroup in another neighborhood (or neighborhoods).
* Displaced persons in a neighborhood are made unwelcome, and move along to another neighborhood.
* People from a group in one neighborhood trickle into another neighborhood over a period of days or weeks.
* Nomadic peoples travel from one neighborhood to another and back again over the course of the year.
* People engage in mass pilgrimages, and then return home.

Note that these use cases are not implemented in GRAM as such; they are the province of the client model, e.g., Athena. But GRAM now provides the infrastructure to support them.

The following scenarios are not yet supported by GRAM:

* First-wave/second-wave friction, i.e., members of group A come to neighborhood N in two successive waves, A1 and A2. (Practically speaking, A1 is probably in N at time 0; A2 comes to N seeking refuge.) Being essentially the same group, A1 and A2 would have a high relationship, which rules out significant friction. This scenario will require a model of dynamic relationships.

#### Dynamic Operations

The application must be able to move a group from one neighborhood to another, split out a new group from an existing group, and transfer population from one group to another (provided that the two groups share a common ancestor). The following portions of GRAM must be considered when performing these operations:

**Group Relationships.** How does the change affect the group's relationships with other groups?

**Attitude Levels.** How does the change affect the group's satisfaction and cooperation levels.

**Pending Attitude Effects.** The group likely has pending level and slope effects on its satisfaction and cooperation curves. How does the change affect these?

**History.** GRAM keeps a record of the contributions to each attitude curve at each time advance, along with other data. How do the changes in the group affect the recording of and access to historical data?

**Existing Drivers.** If a group moves or a new group is formed, how is it affected by existing attitude drivers in its neighborhood?

**The Change as a Driver.** The reason for the change to the group might be an attitude driver in its own right, and will therefore affect the group's attitudes.

#### Moving a Group

The first operation is moving an entire group *g* from neighborhood *m* to neighborhood *n*.

**Rationale:** It is unlikely that a large, established group will move from its home neighborhood in its entirety; usually some remnant would be left behind. But a small group of displaced persons might be forced to move *en masse* from one neighborhood to another.

|  |  |
| --- | --- |
| **Group Relationships** | No change |
| **Attitude Levels** | No change |
| **Pending Attitude Effects** | Discarded. See Section 4.6.6. |
| **History** | The group retains its history. |
| **Existing Drivers** | The application must apply existing drivers to group *g* in neighborhood *n*. GRAM does not have enough information to do it automatically. |
| **The Change as a Driver** | If the movement itself is due to a driver, the application must apply the driver to group *g* once it has been moved. |

#### Splitting a Group

The second operation is to split out a new group *g* from group *f*, placing *g* in neighborhood *n*. Then, *g* is said to be the *child* of *f*, and *f* to be the *parent* of *g*.

A group's ultimate parent is called its *ancestor*; the model often cares whether two groups have a common ancestor. For convenience, the groups created at initialization have no parent, but are considered their own ancestors.

**Rationale:** It will be common for combat, joblessness, etc., to drive people from their homes. We will split out new child groups to represent the displaced subset, so that they can take their attitudes with them.

|  |  |
| --- | --- |
| **Group Relationships** | Copy parent's relationships. |
| **Attitude Levels** | Copy parent's attitude levels. |
| **Pending Attitude Effects** | Do not copy the parent's pending attitude effects. See Section 4.6.6. |
| **History** | History begins for the new group. |
| **Existing Drivers** | The application must apply existing drivers in neighborhood *n* to the new group *g*. GRAM does not have enough information to do it automatically. |
| **The Change as a Driver** | If the split itself is due to a driver, the application must apply the driver to group *g* once it has been created. |

#### Transfer Population between Groups

The third operation is to transfer population from group *e* to group *f*. Note that *e* and *f* must have a common ancestor, so that they have the same relationships.

**Rationale:** First, when population shifts due to combat or other bad circumstances, the shift will often take place a little at a time. We don't want to have to split out a new group each time an increment of population moves from neighborhood *m* to neighborhood *n*. Second, displaced persons can move back home, back to the group they came from.[[21]](#footnote-21) Third, nomads move from neighborhood to neighborhood over the course of the year. We can model this as movement of the entire group, or by splitting two or more groups out of a parent and moving population around.

|  |  |
| --- | --- |
| **Group Relationships** | Are unaffected. |
| **Attitude Levels** | Group *e'*s attitudes are unchanged.  Group *f'*s attitudes are the average of *e'*s and *f'*s before the population shift, weighted by the proportions of *e'*s and *f'*s personnel in *f* after the shift. |
| **Pending Attitude Effects** | Do not copy the parent's pending attitude effects. See Section 4.6.6. |
| **History** | Each group retains its history. |
| **Existing Drivers** | If group *f* was alive before the shift, the application must apply existing drivers whose effect is affected by the change in population; for example, coverage fractions might change. This is standard behavior already, however, and so nothing special need be done.  If group *f* was dead before the shift, then existing drivers need to be applied to *f* as though it were a new group. |
| **The Change as a Driver** | If the shift itself is due to a driver, the application must apply the driver to groups *e* and *f* after the shift. |

#### Pending Attitude Effects

Pending attitude effects are level and slope effects resulting from satisfaction and cooperation inputs. These effects are applied to the relevant attitude curves over time, possibly after a delay. As described in the previous sections, groups that move lose their pending attitude effects, and new child groups begin with no pending attitude effects. This section explains why this is a reasonable solution.

Pending attitude effects are due to attitude drivers, of which there are two kinds: situations and events. Situations generally give rise to slope effects, and events to level effects. We will consider them in turn.

Situations are on-going circumstances in neighborhoods. A group is affected by whatever situations are present in its vicinity. Thus, a moved or newly created group needs to be affected by the situations in its new locale. The situations affecting a moved group in its former location, or a parent group, are not relevant.[[22]](#footnote-22) Thus, pending situation effects can be discarded.

Events are one-time happenings whose attitude effects play out over (a usually rather short) period of time. At first glance it seems appropriate to let a moved or newly created group retain its event effects or those of its parent. At second glance, though, it becomes clear that event effects are of two types: those that affect the group purely because of its location, and those that affect the group because of the group it is. Level effects resulting from power outages are in the former category; level effects resulting from civilian casualties are in the latter category. It makes sense to retain the latter but not the former; and GRAM at present has no way to distinguish between the two categories. Thus, for simplicity we will discard the latter with the former. We can revisit this decision at a later time, if it becomes an issue.

For now, consequently, moved groups and newly create child groups will have no pending attitude effects until existing drivers are applied to them.

#### Dead Groups and Neighborhoods

In the past, GRAM has forbidden groups with zero population. As groups are split, as population is transferred from one group to another, and as population is lost due to attrition in the client simulation, however, zero population is likely to occur. Rather than artificially maintaining at least one person in each group, as we've done in the past, we'll do the following:

* A group with 0 population is said to be *dead*; other groups are *alive*.
* GRAM will check for dead groups at each time advance.
* A group that is dead will lose all of its pending attitude effects: there's no one left to care.
* A group that is dead will receive no new attitude effects.
* No attitude history will be recorded for dead groups.

If groups are allowed to have zero population, then neighborhoods can have zero population.

This primarily affects the computation of neighborhood mood and of neighborhood cooperation with force groups, thus:

* The mood of a zero-population neighborhood is defined to be 0.
* The cooperation of a zero-population neighborhood with any force group is also defined to be 0.

### History

The ultimate effect of any attitude driver (i.e., an event or situation) is remarkably hard to predict. Because of the effects of scaling and causal analysis (Section 4.1.5) the actual contributions of the driver depend on the current attitude levels, along with everything else going on at the same time. In order to assess the actual contributions of any given driver after the fact, then, GRAM preserves a history of the actual contributions of each driver on each satisfaction and cooperation curve at each time tick. This history table can be used to produce a list of the most significant drivers over a certain period of time, with respect to any particular group or neighborhood.

GRAM also preserves the history of each civilian group's population and neighborhood of residence at each time advance, as they are required for the computation of neighborhood statistics over time.

## Relationship Multiplier Functions

A client simulation's attitude rule sets will usually model many kinds of effects that depend on the relationships between acting groups and affected groups. The strength of the effect depends on the relationship *R* between two groups, as mediated by one of a number of *Relationship Multiplier Functions* (RMFs). Given a relationship value *R*, where , each RMF returns a multiplier *r*. This *r* is typically multiplied by the nominal magnitude of an attitude input to produce the actual input.

### Nominal Relationships

At one time, RMFs were computed such that -1 <= r <= 1; the **Linear** RMF, for example, returned 1 for *R* = 1 and -1 for *R =* -1. Thus, applying an RMF to an attitude input reduced the size of the input for anything but extreme relationships. Moreover, extreme relationships simply aren't used:[[23]](#footnote-23) the practical range is more like , Thus, applying any RMF but **Constant** to an attitude input was tantamount to reducing the change by a factor of about 0.6. As a result, the change magnitudes shown in the client simulation's rules were misleading. One would expect a nominal change of 10.0, for example, but the actual change would always be smaller. This made it more difficult for casual users to analyze the probable effect of rule firings, and also complicated the process of getting rule inputs from our subject matter experts.

Consequently, each of the RMFs depends on a parameter[[24]](#footnote-24) called , where . This is the *nominal relationship*, the relationship that the subject matter experts should keep in mind when writing attitude rules. When , we expect the RMF to return 1.0 (or -1.0) and thus have no effect on the outcome. As a side effect, RMFs can return values greater than 1.0 and less than –1.0. An RMF can therefore weaken an input, strengthen an input, change its sign, or leave it unchanged, based on the relationship value *R*.

Specific Relationship Multiplier Functions

Mars defines the following RMFs:

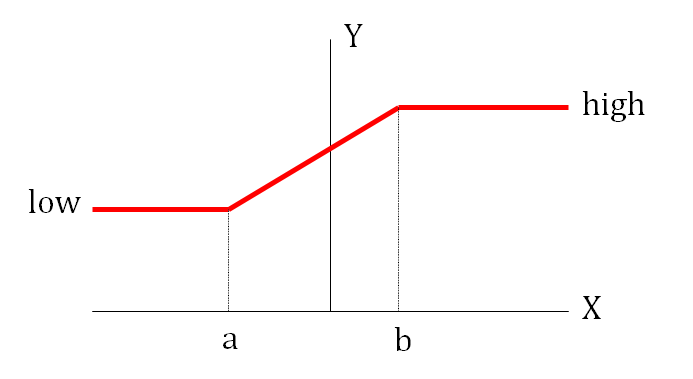
|  |  |
| --- | --- |
| **Constant:** The "Constant" function returns a constant 1.0, regardless of *R*. It is provided for use in generic code that takes the name of the RMF as an input, to remove the effect of group relationships. |  |
| **Linear:** The "Linear" function returns a value directly proportional to the relationship. Use this function when the sign and strength of an effect should match the sign and strength of the relationship. The resulting *r* will have a positive effect on friends and a negative effect on enemies, in proportion to the strength of the relationship. |  |
| **Quad:** The "Quad" function is similar in effect to the "Linear" function; however the resulting effect will be weaker than "Linear" for and stronger than "Linear" for . It is computed as follows: |  |
| **Friends Quad:** The "Friends Quad" function has an effect that is strong for strong friendships, very weak for weak friendships, and zero for enemies of any degree. Its shape for friendly relationships is identical to the "Quad" function. |  |
| **Friends More:** The "Friends More" function has a positive effect on both friends and enemies, but friends are affected much more strongly than enemies. |  |
| **Enemies Quad:** The "Enemies Quad" function has an effect that is strong for strong enemy relationships, weak for weak enemy relationships, and zero for friends of any degree. Its shape for enemy relationships is similar to "Quad", but it does not reverse the sign. |  |
| **Enemies More:** The "Enemies More" function affects both friends and enemies in the same direction, but friends are affected much less than enemies. Like "Enemies Quad", it does not reverse the sign. |  |

## Miscellaneous Models and Algorithms

This section documents models and algorithms of general use.

### Z-Curve Functions

A Z-curve is a stylized S-curve represented as a piece-wise linear curve of three segments. It is defined by the four parameters shown here:



In other words,

### Poisson Processes

In a Poisson process, the probability that a single event will occur during *any* very small interval of time is constant, whether other events have occurred recently or not. The average rate of occurrence, , determines that probability. The probability that *n* events will occur during an interval of length *t* is given by:

If the interval of time is always the same, the formula can be used to restate this formula for the probabilities recursively as follows:

### Selecting a Random Location in a Neighborhood

Use the following algorithm to select a random location in a neighborhood's polygon.

Let *tries* = 10.

While *tries* > 0,

Select a point *p* randomly from the neighborhood's polygon's bounding box.

If point *p* lies within the polygon, taking overlapping neighborhoods into account,

Return point *p*.

Done.

Otherwise, decrement *tries*.

If no point has been found in 10 tries,

Return the neighborhood's reference point.

Done.

# Appendices

## Acronyms

AUT Autonomy

BCTP Battle Command Training Program

CTR Contractor

CUL Culture

GRAM Generalized Regional Attitude Model

IGO Inter-Governmental or International Organization

JNEM Joint Non-kinetic Effects Model

JRAM JNEM Regional Analysis Model

MAG *Mars Analyst’s Guide*

MAM Mars Affinity Model

NGO Non-Governmental Organization

NSC National Simulation Center

QOL Quality of Life

TRADOC Training and Doctrine Command

TRISA TRADOC Intelligence Support Activity

RAM Regional Analysis Model

RMF Relationship Multiplier Function

SFT Safety

1. Note that these proximities are social, not geographic—proximities are input to URAM, and are not computed from the geometry of the neighborhoods or the distance from one neighborhood to another. [↑](#footnote-ref-1)
2. This scale is implemented by the qposition type in simtypes(n). [↑](#footnote-ref-2)
3. This scale is implemented by the qemphasis type in simtypes(n). [↑](#footnote-ref-3)
4. We had originally thought that if were zero for some some topic *i,* then that topic should have no effect on . Later we realized that group *f* would still care about the groups around them, even if they did not care about *i.*  [↑](#footnote-ref-4)
5. See the memo “Mars Affinity Model”, by William H. Duquette (whd12\_002), 1 February 2012, for the derivation of these special cases. [↑](#footnote-ref-5)
6. Adjustments of this sort were originally implemented in JRAM to support course corrections during training with JNEM. Athena v4 supports adjustments, but the capability is only intended as an aid to testing. [↑](#footnote-ref-6)
7. It is expected that the client software will assign names to the causes; but for purposes of applying effects to curves it is more efficient to use integer IDs. [↑](#footnote-ref-7)
8. Remember that the adjustments were applied to the baseline between time advances. [↑](#footnote-ref-8)
9. There shouldn’t be any, but if there are then has already been changed by the client simulation and we must accommodate that. [↑](#footnote-ref-9)
10. Defined in the model parameter database as gram.epsilon. [↑](#footnote-ref-10)
11. A *situation* is an on-going condition, known to the client simulation, that has satisfaction implications for as long as it lasts. [↑](#footnote-ref-11)
12. And, in fact, it's implemented as a single effect, which contains a list of future start times and slopes. [↑](#footnote-ref-12)
13. This scale is implemented by the simlib(n) type qsat. [↑](#footnote-ref-13)
14. Gurr defines *salience* as "the strength of motivation to attain or maintain the desired value position" in *Why Men Rebel*, Ted Gurr, Princeton, NJ: Princeton University Press. 1970, p. 66. This book was a seminal source for the original RAM model. [↑](#footnote-ref-14)
15. Note that small elites can matter out of proportion to their size. Thus, we used to use a "rollup weight" instead of the actual population; the rollup weight was intended to be based on the population, but be modified for special cases. Experience reveals that the users usually left the rollup weight set at its default value of 1.0, so that not even population was being taken into account. Consequently, we are now using population explicitly, and will add an *elite factor* in as a separate term if and when it becomes necessary. [↑](#footnote-ref-15)
16. "Satisfaction Roll-Up", Robert G. Chamberlain, September 12, 2006 [↑](#footnote-ref-16)
17. Ambassador Terry McNamara has pointed out that "collaboration" is a loaded word, and that a more neutral term is preferable. [↑](#footnote-ref-17)
18. The proximity limit is found in the model parameter database as “gram.proxlimit”. [↑](#footnote-ref-18)
19. Model parameter: gram.coopRelationshipLimit, nominally 1.0. [↑](#footnote-ref-19)
20. The civilian group's perception of the relationship between *h* and *g* is likely to be inaccurate. For, now, though, the actual relationship is what we have and we are using. [↑](#footnote-ref-20)
21. Until we have dynamic relationships, there's no benefit to making the returnees a separate group; and even when we do, it will sometimes be appropriate for the returnees to join their original group. [↑](#footnote-ref-21)
22. A child group can be split out in the same neighborhood as its parent; in this case, it might be reasonable to let it copy its parent's pending situation effects. But the application of existing drivers will have the same net effect, and there's no reason to right special purpose code for this rare case. [↑](#footnote-ref-22)
23. Two groups with a relationship of 1.0 might as well be the same group; we usually only see values of 1.0 for the relationship of a group with itself. And a relationship of -1.0 is literally insane. If two groups A and B have a relationship of -1.0 then A is precisely as angered about something good that happens to B as B is pleased about it. [↑](#footnote-ref-23)
24. Model parameter: rmf.nominalRelationship [↑](#footnote-ref-24)