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"Collective C2 in Multinational Civil-Military Operations"
Title: Organizational Agility Model and Simulation
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Multiple Governance and Management (GM) approaches such as de-conflicted, coordinated, collaborative, and "edge" may all be required during complex endeavours in order to meet mission objectives effectively and efficiently. GM Approach agility is defined as an entity's (individual, team, organization, or collective) ability to transition between one GM Approach and another and to maintain that approach in the presence of disturbances, uncertainty, and self-damage. A conceptual model for GM Approach transitions is programmed into a computer simulation, demonstrating the dynamic nature of the agility concept. The model is refined using simulation, yielding a logical and internally consistent dynamic model that obeys a GM Approach Space "Law of Motion", and employs behaviours improve the transition response.

The model and simulation was not developed to find numerical equivalents for socio-technical-organizational complexities. Rather this study provides a means to visualize the transition yielding key insights into GM Approach agility. For instance, entity size, resistance to transition, and stiffness (comfort level at a particular approach) determine the transition system's stability and response profile. Also, compensatory, anticipatory, adaptive, and learning behaviours (methods) are employed to modify stiffness and resistance, stabilize naturally unstable systems, improve responsiveness, provide resilience and known and unknown disturbance rejection, as well as optimize transition effectiveness and efficiency. Eventually, the model and simulation may be used to formulate recommendations for GM Approach agility strategic investments as part of comprehensive approaches to complex endeavours.

Introduction

In 2010 the world experienced major natural disasters (Haiti and Pakistan Floods), major conflicts (Afghanistan, Iraq), and major events (Olympics, G8 and G20 summits). These events have been characterised as complex endeavours: both complex in the environment and in "self" (SAS-065, 2010)[1]. The response to these events involved multiple organizations forming a collective whose overall objective was to minimize disruptions and return to or maintain social stability. The collective govern and manage themselves so that they work together to achieve the desired outcomes. However, different Governance and Management (GM) Approaches[2] or styles may be required at different points in time depending on the level of situation complexity. That is, no single GM Approach may be effective or efficient for all phases of the endeavour.

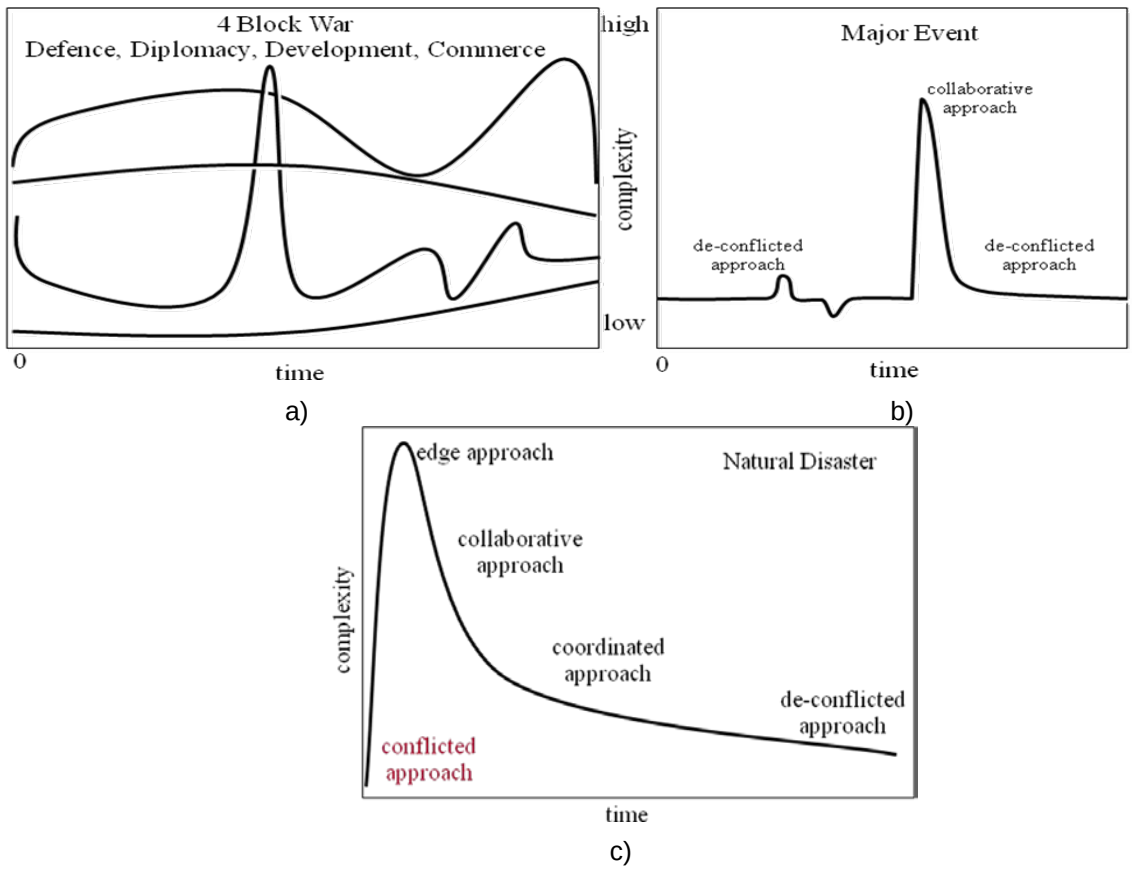


Figure 1: Hypothetical Complexity Profiles for Three Different Complex Endeavours

For example, if an event's complexity level could be measured over time, a high intensity conflict may look like Figure 1a with four lines of operation, Defence, Diplomacy, Development, and Commerce (Government of Canada, 2005) and overlapping complexity profiles. The hypothetical profile in Figure 1b shows some complexity changes for a major sporting event or

[1] Environment complexity involves the stability and predictability of the situation (to name a few from the reference) while "self" complexity includes the number of entities within a collective that have different values, cultures, languages, and levels of trust (to name a few from the reference).

[2] Governance and Management (GM) is meant to be a more generic term than Command and Control (C2), which would resonate with collectives comprising both non-military and military partners.

heads of state meeting where the hope is to conduct an event that is well under control with minimal disturbances requiring a de-conflicted GM Approach. GM Approach agility suggests that a collective would need to transition to a collaborative GM Approach to successfully cope with any significant disturbances that cause an increase in complexity, in order to reduce the situation complexity.

Figure 1c shows a hypothetical Natural Disaster complexity profile. Superimposed are plausible GM Approaches required as the event unfolds. At the beginning of the event (tsunami, earthquake, etc.) there may be total chaos with no GM coordination within the collective at all (conflicted approach). However, edge-like approaches may be required to deal with the chaos. Over time a collective moves from edge to collaborative, coordinated, and finally de-conflicted, which is the most effective and efficient approach particularly in stable situations. A complete discussion of the various approaches and their definitions are found in (SAS-065, 2010).

Why introduce the notion of GM Approach agility? Why is it necessary to transition from one approach to another? Why not operate at an edge GM Approach all the time? While operating at edge may be effective in high complexity situations they require significant strategic and long-term investments in policies, processes, human resources, technologies, infrastructure, and training in order for the organizations to work together. Also, edge approaches are excessive for simpler situations that only require de-conflicted, for example. Thus, GM Approach agility provides the means to select a GM Approach commensurate with situation complexity, thus maximizing effectiveness and efficiency.

This notion of agility involves motion in the GM Approach space over time and therefore lends itself to modelling and simulation. Modelling and simulation forces us to develop a logical concept in terms of variables as a function of time. It helps us visualize the relationships between GM Approaches and their dimensions, organizational forces involved in transitioning in the GM Approach space, key organizational parameters and parameter modifiers (entity behaviours or methods) related to the transition, and GM Approach effectiveness and efficiency. It helps us articulate those parameters and modifiers that make the collective more or less agile.

This paper reports on the development of a model and simulation for GM Approach agility defined as the ability to transition from one GM Approach to another as required by situation complexity. The paper begins with defining GM Approach agility and introducing the GM Approach space. The second section provides an analogy between transitions in the GM Approach space to motion in Physical space. This description leads to identifying entity size, stiffness, and resistance as key parameters that determine the entity's stability and responsiveness as it moves through the GM Approach space. The third section employs Control Theory to solve a classical motion tracking problem using compensatory, anticipatory, adaptive, and learning behaviours. These behaviours modify the size, resistance, and stiffness parameters that lead to improved robustness and responsiveness as well as resilience and disturbance rejection. The final section discusses GM Approach effectiveness and efficiency.

GM Approach Agility Definition and GM Approach Space

The first paper of the Organizational Agility series used a spring-mass-damper motion system as a metaphor for the organization's dynamic response, and identified twelve organizational attributes related to agility: configuration potential, robustness, resilience, responsiveness, innovation, flexibility, size, resistance/willingness to change, compensatory, anticipatory, adaptive, and learning methods (Farrell & Connell, 2010). We know instinctively that these attributes are related to the transition dynamics from one Approach to another in the GM Approach space. However, in this paper these relationships are developed further from first principles based on laws of motion and Control Theory. The resultant model is logical, internally consistent, brings clarity to the attributes as they relate to the transition and each other, and allows us to simulate the Approach transition dynamics.

The simulation model development begins with defining agility. NATO Research Task Group SAS-065 entitled "NNEC C2 Maturity Model" defined agility as the ability to transition between GM Approaches as well as "Being able to choose among a larger set of C2 approaches" (SAS-065, 2010). SAS-085 entitled "C2 Agility and Requisite Maturity" provided a working definition for agility as the ability to successfully cope with changes in the environment[3]. "Changes in the environment" refers to different complexity levels requiring different coping strategies. "Ability to cope" means those organizational attributes (such as a GM Approach) that help an organization deal with situation complexities. "Successfully cope" involves effectiveness and efficiency at all levels – from GM Approach transitions to mission success.

This paper's working definition retains the essence of the SAS-065 and SAS-085 definitions as follows: GM Approach agility is the ability to transition from one GM Approach to another as required by situation complexity, in a manner that optimizes GM Approach effectiveness and efficiency. This paper focuses only on the agility associated with transitioning from one GM Approach to another, while SAS-085 considers all aspects of agility and successfully coping in a changing environment.

This definition resembles a classical motion tracking problem commonly described by Newton's laws of motion for an object moving in physical space. Control Theory provides methods to the tracking problem that modify key parameters and optimize effectiveness and efficiency. The key GM Approach agility concepts are:

- GM Approach Space
- GM Approach Law of Motion
- GM Approach Transition Methods
- GM Approach Transition Effectiveness and Efficiency

As mentioned, GM Approach agility involves moving from one position to another in the GM Approach space. The GM approach space involves three dimensions (Figure 2):

- Allocation of Decision Rights (ADR) extends from none to broad,
- Distribution of Information (DI) extends from none to broad, and
- Patterns of Interaction (PI) extends from tightly[4] constrained to unconstrained.

[3] This working definition was formulated in Paris, 2010 and continues to morph, but retains the idea of transitioning from one approach to another.

[4] It is recommended that this anchor be changed from "tightly constrained" to "completely constrained" to reflect the exact opposite of "unconstrained".

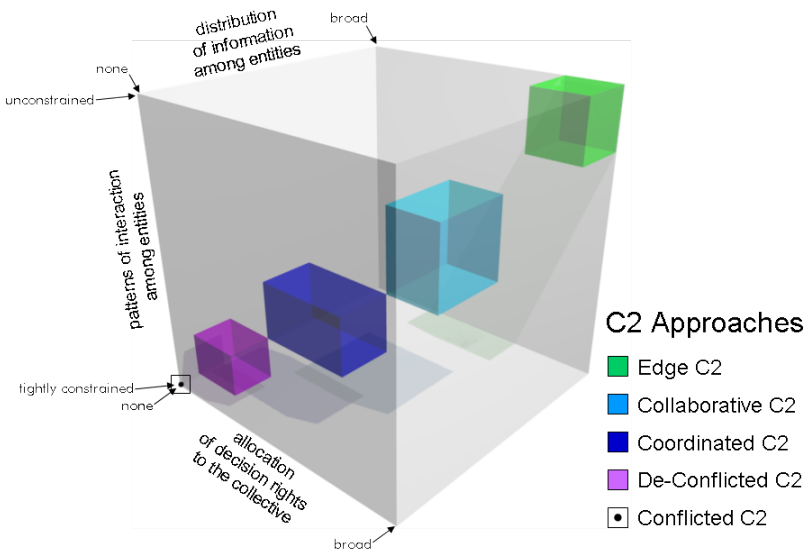


Figure 2: C2 Approaches and the C2 Approach Space (SAS-065, 2010)

A position in this space represents a GM Approach. For example, at the origin ADR is none, DI is none and PI is tightly constrained, or (none, none, tightly constrained), which defines a conflicted GM Approach. Table 1 is a categorical table that provides five representative GM Approaches in terms of ADR, DI, and PI values. These approaches lie along the diagonal of the GM Approach space: Conflicted[5] (Independent), De-conflicted, Coordinated, Collaborative, and Edge approaches.

C2 Approach	Allocation of Decision Rights to the Collective	Patterns of Interaction Among Participating Entities	Distribution of Information (Entity Information Positions)
Edge C2	Not Explicit, Self-Allocated (Emergent, Tailored, and Dynamic)	Unlimited As Required	All Available and Relevant Information Accessible
Collaborative C2	Collaborative Process and Shared Plan	Significant Broad	Additional Information Across Collaborative Areas/Functions
Coordinated C2	Coordination Process and Linked Plans	Limited and Focused	Additional Information About Coordinated Areas/Functions
De-Conflicted C2	Establish Constraints	Very Limited Sharply Focused	Additional Information About Constraints and Seams
Conflicted C2	None	None	Organic Information

Table 1: Variables Defining Collective C2 Approach (SAS-065, 2010)

[5] It is recommended that Conflicted GM Approach be changed to Independent GM Approach. It was observed in the Olympics case study that collectives were at the origin (none, none, tightly constrained) and exhibited non-conflicting, conflicting, and anarchical behaviours.

Although SAS-065 and SAS-085 focus primarily on these five approaches, the model developed herein can be extended to include the entire GM Approach Space.

Note well from Table 1 that the GM Approach Space has gaps where, theoretically an approach does not exist: between Conflicted and De-Conflicted GM Approach, and between Collaborative and Edge GM Approach. This means that the dimensions are discontinuous. These discontinuities are modelled by using a filter that converts smooth and continuous transitions into discrete transitions according to Table 1.

GM Approach Space Law of Motion

Transitioning from one GM Approach to another means that an entity must broaden or narrow their allocation of decision rights, broaden or narrow their distribution of information, or loosen or constrain their patterns of interaction. For this initial modelling and simulation development, the entity moves along all three dimensions at the same time, and generally along the diagonal of the space. However, it takes time to broaden and narrow, or loosen and constrain when moving from one GM Approach. The transition is not instantaneous rather it involves transient and steady state responses.

It is postulated that motion in the GM Approach space is governed by organizational forces that enable or oppose the entity from moving from one approach to another. The enabling force, or the forcing function[6], is the required GM Approach as determined by situation complexity. Once the entity begins to change its ADR, DI, and PI states, it starts to gather momentum and move towards the required GM Approach. However, organizational forces – both internal and external to the entity (e.g., trust, slow internet services, comfort level with approach, etc.) – resist the motion and act to restore the entity to a more familiar approach. Thus, it is postulated that an entity has a Forcing Function, and Resisting and Restoring Forces acting on it as it moves from one position to another in the GM Approach space.

Newton's 2nd law of motion states that the time rate of change of an object's momentum (mass × speed) is equal to the sum of forces acting on the object. The equivalent law of motion in the GM Approach space is that the time rate of change of an entity's momentum (size × speed) is equal to the sum of forces acting on the entity. Given this law of motion, a conceptual equation can be generated that governs the transient and steady state position of a GM Approach as it moves in the GM Approach space. But before presenting the governing equation, a few ideas need to be defined that have equivalent concepts of an object moving through physical space:

Position, speed, and acceleration

- $x(t)$ is the current or actual position in the GM approach space as a function of time.
- $x_o(t)$ represents the entity's most comfortable GM Approach at minimum internal stress.
- $v(t)$ is the speed, or rate of change of position in the GM approach space, $\dot{x}(t)$.
- $a(t)$ is the acceleration, or rate of change of the speed in the GM approach space, $\ddot{x}(t)$.

[6] Case studies show that the entity's leader compels the collective to adopt their desired GM Approach, which may override the required GM Approach if the leader has not taken into consideration the changing situation complexity.

Size, momentum, and rate of change of momentum

- m is defined as entity size. This parameter represents the number of people, resources, equipment, infrastructure, funds, etc., that the entity possesses.
- mv(t) = $m\dot{x}(t)$ is the entity momentum.
- ma(t) $= m\frac{dv}{dt} + v\frac{dm}{dt} = m\ddot{x}(t) + \dot{m}\dot{x}(t)$ is the time rate of change of entity momentum.

Required position and Forcing Function

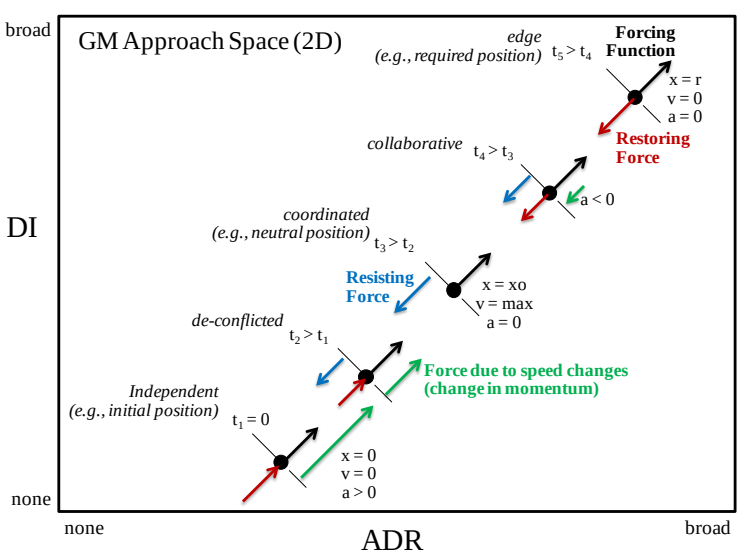
- r(t) is the required position in the GM approach space as a function of time (see Annex A).[7]
- $k(r - x_o)$ represents the Forcing Function.

Stiffness and Restoring Force

- k is defined as entity stiffness. This parameter represents the restoring strength. That is, if the entity very comfortable with, say, a Coordinated approach but not at all comfortable with all other approaches, then k is high. If the entity is equally comfortable with all approaches, then k is low. Most organizations have a high k because they operate only at one approach.
- $-k(x - x_o)$ is a Restoring Force that exerts an opposing force as a function of position away from the comfortable position. The larger the k, the larger the force like a stiff spring.

Resistance and Resisting Force

- c is defined as entity resistance. This parameter represents <u>external</u> resistors, such as slow internet services, lots of bureaucracy, intermittent power outages, etc., and <u>internal</u> entity resistors, such as culture, values, interaction preferences, (lack of) trust, experience with GM Approaches, etc., that resist the entity motion through the space.
- $-c\dot{x}(t)$ is a Resisting Force that exerts an opposing force when moving through the GM Approach space ($\dot{x} \neq 0$). The larger the c, the larger the force like moving through molasses.



[7] There is no attempt to determine the transfer function between situation complexity and r(t) in this paper. However, the simulation allows the user to generate r(t) profiles that reflect changes in situation complexity.

Figure 3: Forces acting on entity as it transitions from independent to edge GM Approaches.

Figure 3 summarizes and illustrates these concepts by showing the magnitude and direction of the forces on the entity that has a neutral position of Coordinated, as it transitions from Independent to Edge positions at five snapshots in time. Applying the 2nd law of motion yields the following governing equation for an entity as it moves through the GM Approach space:

$$\mathbf{ma} + \dot{\mathbf{m}}\dot{\mathbf{x}} = \sum \mathbf{F} \tag{1}$$

$$\mathbf{m}\ddot{\mathbf{x}} = \mathbf{k}(\mathbf{r} - \mathbf{x_o}) - \mathbf{k}(\mathbf{x} - \mathbf{x_o}) - (\mathbf{c} + \dot{\mathbf{m}})\dot{\mathbf{x}} \tag{2}$$

$$\mathbf{kr(t)} = \mathbf{m}\ddot{\mathbf{x}}\mathbf{(t)} + \mathbf{c}\dot{\mathbf{x}}\mathbf{(t)} + \mathbf{kx(t)} \ \ldots \mathbf{for}\ \dot{\mathbf{m}} = \mathbf{0} \tag{3}$$

Equation 3 represents the time varying dynamics as an entity transitions from one GM Approach to another. Assuming that the entity size does not change ($\dot{\mathbf{m}} = 0$)[8], the variables involved in this transition include the actual position, speed, and acceleration in the GM Approach space, the entity size, resistance, and stiffness associated with entity momentum changes, resisting and restoring forces, and the required position and resultant forcing function. Note that when the position is not moving ($\ddot{\mathbf{x}} = \dot{\mathbf{x}} = \mathbf{0}$), x = r and the Restoring Force is equal and opposite to the Forcing Function (i.e., force equilibrium is achieved). Also note that $x_o = x_o(t)$ may migrate over time, however, this does not factor into the governing equation.

Natural Frequency and Damping Ratio

The governing equation contains all information regarding the dynamics, that is the position time profile x(t), as the entity transitions from one position to another. The parameters, m, c, and k fully determine the stability of the transition as well as whether the response will be under-damped (converges onto r(t) in an oscillatory fashion) or over-damped (exponentially converges onto r(t)).

Equation 3 is normalized with respect to size as follows:

$$\omega_n^2\mathbf{r} = \ddot{\mathbf{x}} + 2\xi\omega_n\dot{\mathbf{x}} + \omega_n^2\mathbf{x} \tag{4}$$

where $\omega_n = \sqrt{\mathbf{k}/\mathbf{m}}$ and $\xi = 0.5\,\mathbf{c}/\sqrt{\mathbf{mk}}$, are the entity's natural frequency and damping ratio. The natural frequency characterizes how well the system tracks a sinusoidal path, r(ωt). For $\omega_n \gg \omega$, the system tracks the required path as shown in Figure 4 with bounded steady state error (under-damped: ξ = 0.35 < 1). For $\omega_1 n \ll \omega$, k is reduced 100 times and the system cannot track the forcing function (over-damped: ξ = 7.1 > 1).

The damping ratio (ξ) represents a ratio of Resisting and Restoring forces. The damping ratio is directly related to the Resisting Force, where more resistance (c) means slower movement through the GM Approach space. It is also inversely related to the square root of the Restoring

[8] Although the modelling and simulation runs assumed that the entity size did not change, a case study of the Munich Olympics reported that the collective size did expand which contributed to the Resisting Force. Future software versions may relax the assumption and include this nuance in the modelling and simulation code.

Force, where more stiffness (k) means less damping. That is, the Restoring Force may be so great (high k) that it easily overcomes any resistance in returning to a more comfortable position, while an overly non-stiff organization (low k) cannot overcome large resisting forces.

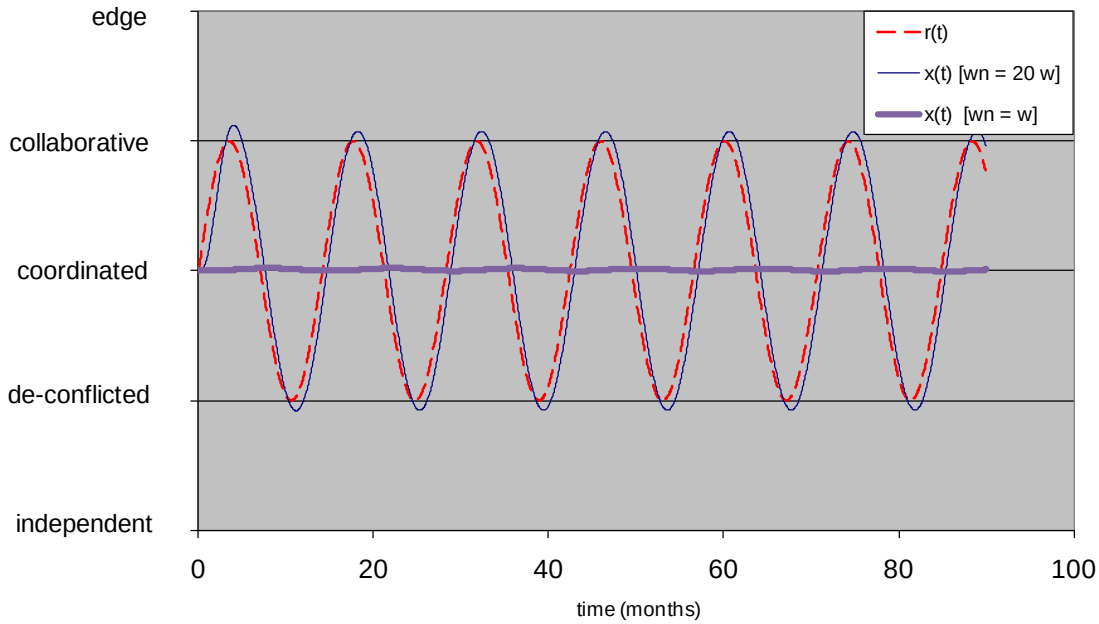


Figure 4: Response to r(ω t) = sin ω t for $\omega_n = 20\omega$ and $\omega_n = \omega$.

Filters for realistic response

Readers who are familiar with differential equations will recognize that Equation 4 produces smooth[9] and continuous[10] time profiles. Realistically, however, only the initial and final steady state GM Approaches are observable and not necessarily every intermediate transient state. Thus, two filters are applied to the x(t) profile derived from integrating the differential equation. The steady state filter retains the steady state value of x(t) only and removes the steady state response. The simulation pseudo code for this filter is given in Figure 5. Alternatively, a 'representative' filter has been developed such that if x(t) passes through or remains within any one of the 5 representative GM Approach regions, then it is set to the region's centre position. The simulation pseudo code is shown in Figure 6.

```
If x = within independent region Then
       xfilter = independent GM Approach

Else If (de-conflicted ≤ x < collaborative) Then
        If (x_ss ≈ r_ss) Then
          xfilter = x_ss (steady state value of x)
        End If

Else If x = within edge region Then
       xfilter = edge GM Approach

End If
```

[9] x(t) has only one value at any given time and does not violate a vertical line test for mathematical functions.
[10] v(t) and a(t) have only one value at any given time: that is, the function derivatives are smooth.

Figure 5: Steady State Filter

```
If x = within independent region Then
       xfilter = independent GM Approach

Else If x = within de-conflicted region Then
       xfilter = de-conflicted GM Approach

Else If x = within coordinated region Then
       xfilter = coordinated GM Approach

Else If x = within collaborative region Then
       xfilter = collaborative GM Approach

Else If x = within edge region Then
       xfilter = edge GM Approach

End If
```

Figure 6: Representative Filter

Figure 7 shows the continuous (blue), steady state (purple) and representative (black) filter responses of x(t) to a required GM Approach time profile, r(t) (red), first introduced in (Farrell & Connell, 2010) and transcribed in Annex A. Note that the regions between independent and de-conflicted, and collaborative and edge are blanked out. This part of the response space does not exist according to Table 1. Note that r(t) peaks at edge between $60 < t < 63$, however, the entity cannot change fast enough within the 3 months before a new approach is required.

A critical difference between the two filters is that at $t > 68$ months the steady state filter response converges onto the required position exactly between De-conflicted and Coordinated (permitted in Table 1). However the representative filter response oscillates between De-conflicted and Coordinated, which is unlikely to occur in the real world. On the other hand, between $60 < t < 63$ the steady state filter response shows that the entity remained at De-conflicted even though the demand was Edge. Meanwhile the representative filter response shows plausible intermediate stages indicating that the entity attempted to move to Edge.

Two important observations are 1), the simulation may incorporate any type of filter that helps visualize GM Approach changes in time, and 2) although the filter determines the final position, the timing of the transition between two positions is still governed by Equation 4. For example, when $0 < t < 20$, the entity moves from Independent to Coordinated in 4.7 months. However, if the Resisting Force is increased by 1.5 ($c_{new} = 1.5c$) then the transition takes 15.3 months (not shown). This model is a powerful tool for determining transition timings for a given size, stiffness, and resistance.

Robustness

"Robustness: the ability [for the entity] to maintain effectiveness across a range of tasks, situations, and conditions" (Alberts & Hayes, 2003). In this context, "maintain effectiveness" means that the steady state error, $e_{ss} = r_{ss} - x_{ss}$ is small and bounded: that is, the transition is stable. "Across a range of tasks, situations, and conditions" means for all required positions, r(t), in the GM approach space.

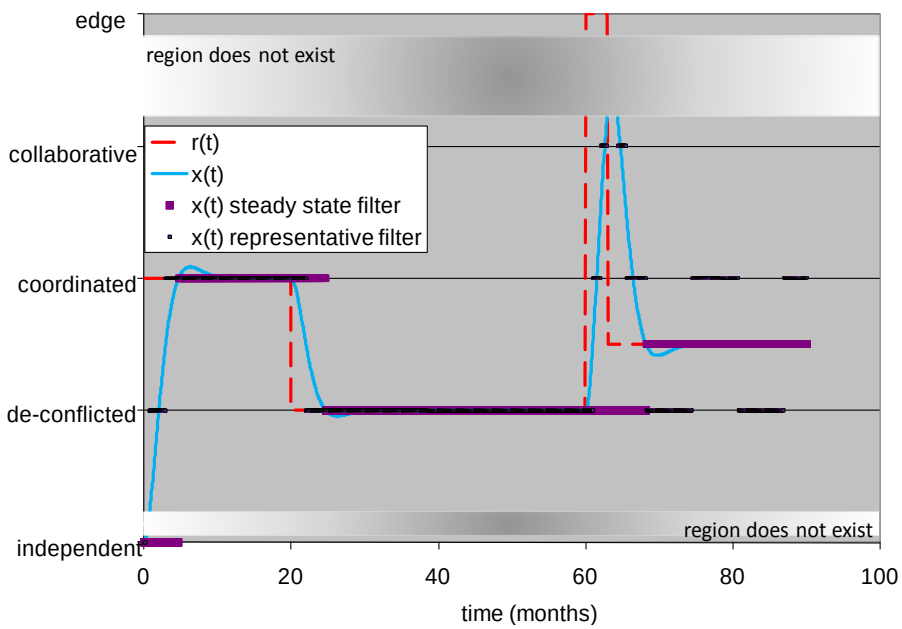


Figure 7: Steady state and representative filters applied to x(t).

A prerequisite for robustness is that the system must be stable. That is, it must be capable of reaching an equilibrium position, $x(t) = x_{ss}$, $v = 0$, and $a = 0$. If the forces acting on the position are unbalanced, then the position will move in the direction of the unbalanced force as shown in Figure 3. Equation 4 is inherently stable for $\omega_n > 0$ and $\xi > 0$ when there are no disturbances or uncertainty. See (Farrell & Connell, 2010; Van de Vegte, 1990) for full proof.

Responsiveness

"... the ability [for the entity] to react to a change in the environment in a timely manner" (Alberts & Hayes, 2003). In the context of the model, the natural frequency and the damping ratio fully characterize the system's responsiveness or response profile. For example, in Figure 7, $\omega_n \approx 0.7$ rad/month, which yields a time period ($= 2\pi/\omega_n$) of 8.8 months, while the demand frequency, $\omega \rightarrow 0$. Thus, at $0 < t < 20$, the entity is able to transition from independent to de-conflicted well within 20 months, but cannot transition from de-conflicted to edge in 3 months ($60 < t < 63$) where $\omega \approx 0.5$ rad/month ($\omega_1 n(\omega$). The entity is responsive to certain demand profiles but not others.

To improve the responsiveness so that the entity has a chance of responding to the high demand requires that the stiffness is increased about 1.5 times, when the characteristic time period becomes 2.8 months (not shown). However, increasing the stiffness means less damping that produces significant overshoot. Getting the balance right between the Resisting and Restoring Forces is the key to optimizing responsiveness as the entity moves from one GM Approach to another.

GM Approach Transition Methods

Agile organizations change their GM approach as the situation complexity changes to ensure GM approach effectiveness; that is x(t) = r(t). This statement is a classical motion tracking problem for the GM Approach space. The discipline of Control Theory (Van de Vegte, 1990) provides methods that minimize error, $e(t) = r(t) - x(t) \rightarrow 0$. Short discussions of other methods that can be used are found in Annex B.

Perceptual Control Theory (PCT) uses Control Theory as the basic framework for describing entity behaviour (Powers, 1973; Powers, Clark, & McFarland, 1960). PCT would suggest that an entity employs feedback control methods that adjust or modify (ADR, DI, PI) and drive the actual GM Approach position, x(t) towards the required GM Approach position, r(t)[11]. These methods ensure robustness, responsiveness, resilience, disturbance rejection, and maintain effectiveness and efficiency despite self-damage, disturbances, and uncertainty. See Figure 8 for a basic representation of feedback control and the major processes around the loop. The comparator function compares the actual and required GM Approaches and generates an error value. The control method (or the equivalent entity behaviour) generates appropriate actions based on the error. Those actions impact on the environment (in this case, the GM Approach space) and influence state values, one of which is the actual GM Approach, thus closing the loop.

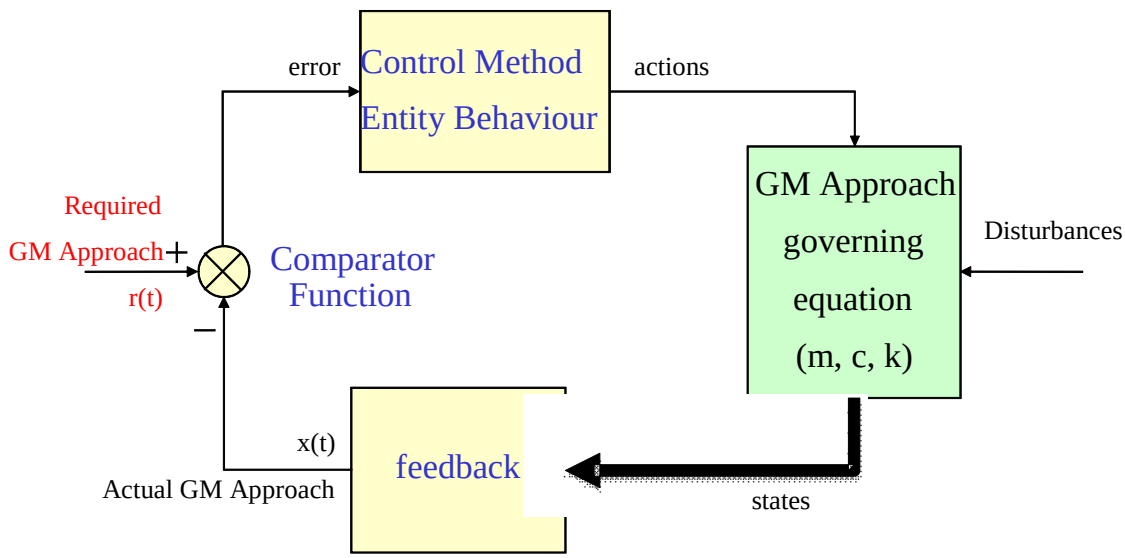


Figure 8: PCT depiction of an entity using feedback control methods to drive x(t) towards r(t).

All types of natural and man-made systems employ feedback control methods to cope with and track required paths through physical and non-physical complex environments (e.g., humans, plants, robots, power plants, complex endeavours, etc.). For example with Figure 8 in mind, a child may be required to stay beside their parent as they walk together for the first time in a busy mall (a classical motion tracking problem). The situation is complex certainly from the child's perspective. The child continually gathers feedback about their surroundings (states), integrates them and generates a perception of the distance between them and their parent, and compares their actual position to the required position – beside their parent. If a position error is greater than zero and the child is behind the parent, the child may compensate (a method or behaviour) for the error and speed up (action) so that they reduce the error.

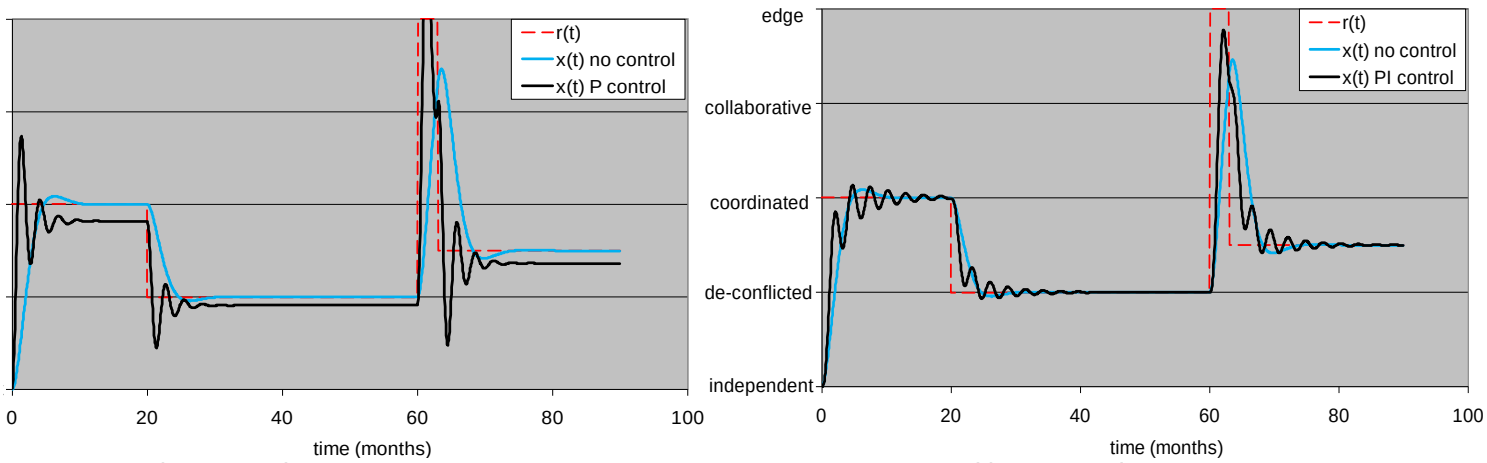
[11] Note well that the error can also be minimized by keeping x(t) steady and modifying r(t).

Note that the child does not need to have any knowledge of the complex environment with all of its constraints, uncertainty, and disturbances in order to apply this simple method. The more complex the environment, the simpler the control methods become. However, more sophisticated methods can be used to improve effectiveness but often at a cost. The child might anticipate the parent's next few footsteps and walk just in front of them. The child might adapt and climb into the stroller the parent is pushing. The child might learn, for the next time, that holding hands achieves the goal. Compensatory, Anticipatory, Adaptive, and Learning methods are well-documented control algorithms (Slotine & Li, 1991; Van de Vegte, 1990) that minimize the error between actual and required positions and solve the tracking problem despite uncertainty and disturbances. Note well that the control methods mentioned above are derived primarily from observing human behaviour and their response to complex situations.

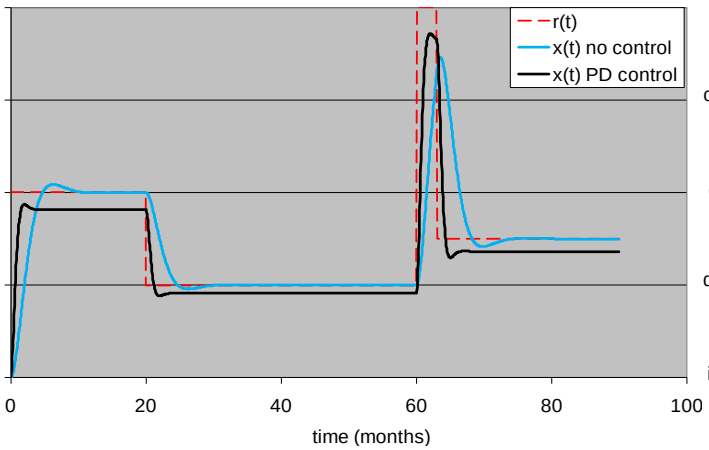
Compensatory Method

Compensatory control methods involve making decisions based on the error magnitude and direction, $K_p e(t)$, where K_p is a positive gain that proportionally amplifies the error magnitude. This method is called proportional (P) control. In the above example, the child used P control to compensate for the error: that is, the error was positive (lagging behind the parent) and they sped up proportionally to the error. If the error were negative (in front of the parent) they would slow down proportionally to the error. The value of K_p determines the dynamic behaviour of moving from the current position to the required position: whether they would ever reach their parent at their slow pace (stability), how long it would take to reach their parent (settling time), and whether they might overshoot the parent by going too fast (under-damped response).

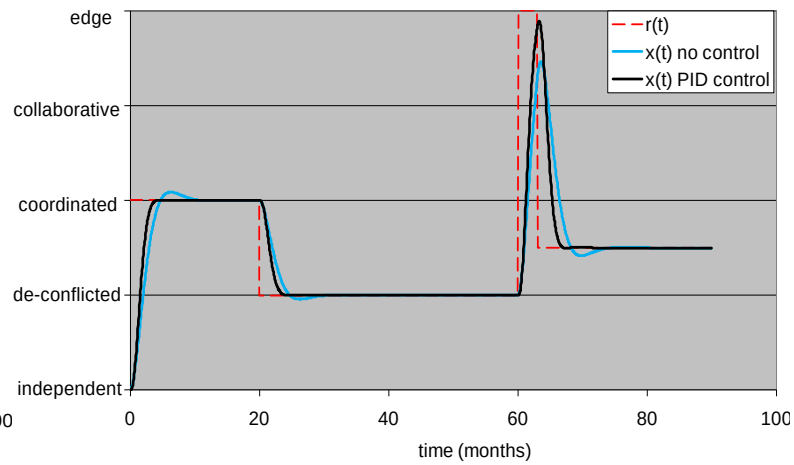
Similarly, an entity can use feedback to generate an error, $e(t) = x(t) - r(t)$, and employ P control to track r(t) in the GM Approach space. If the actual GM approach lags the required GM Approach, $e(t) > 0$, then the entity would broaden and un-constrain (ADR, DI, PI) proportionally to K_p. If x(t) leads or overshoots r(t), $e(t) < 0$, then the entity would narrow and constrain (ADR, DI, PI). P control is simple and yet very effective for tracking r(t). It requires no knowledge of disturbances or variable uncertainty to work. The simulation incorporates four compensatory methods, and these methods are compared to open-loop (no control) response in Figure 9.



a) P Control, $K_p = 10$ b) PI Control, $K_p = 10$, $K_i = 6.7$



c) PD Control, K_p = 10, K_d = 5



d) PID Control, K_p = 10, K_i = 6.7, K_d = 5

Figure 9: Comparing x(t) response profiles without (no control) and with compensatory methods

In Figure 9a, x(t) (blue line) with no control is compared to x(t) (black line) with P control. The P control response exhibits a hunting behaviour (overshoot), but tracks r(t) (red line) with a nonzero steady state error. P control may be extended to include information about the accumulated error history expressed as an integral, $K_i\int e(t)dt$ (I control), and error trend expressed as a derivative, $K_d\dot{e}(t)$ (D control).

PI control drives the steady state error to zero, but induces oscillations (Figure 9b). PD control decreases rise time from 4.7 months for the "no control" condition to 1.6 months, however, the steady state error is non-zero (Figure 9c). PID control produces zero steady state error, no overshoot (critically damped, ξ = 1), and faster rise time (4.1 months) compared to the "no control" condition (Figure 9d). PID control is the most common form of Compensatory methods used to optimize effectiveness and efficiency.

Compensatory methods are used to stabilize unstable systems where a Resisting Force actually accelerates movement through the GM space rather than retards it ($c < 0$), or a Restoring Force actually repels movement away from a neutral position ($k < 0$). With compensatory methods and proper choice of PID gains, an open loop unstable system can be stabilized (Van de Vegte, 1990). Stability is a precondition for robustness. Stabilizing unstable systems is clearly demonstrated in the section on resilience.

Compensatory methods are used to improve responsiveness. K_p, K_i, and K_d effectively set the closed-loop natural frequency and damping ratio to optimal values. If the m, c, and k are known explicitly then Control Theory provides algorithms that yield optimal gain values. Otherwise, sufficient gains can be found using trial and error as done for Figure 9. PCT would argue that humans set "sufficient gains" through trial and error (e.g., a child learning to walk), and they "optimize gains" through learning and practice (e.g., a high performance speed walker).

Resilience

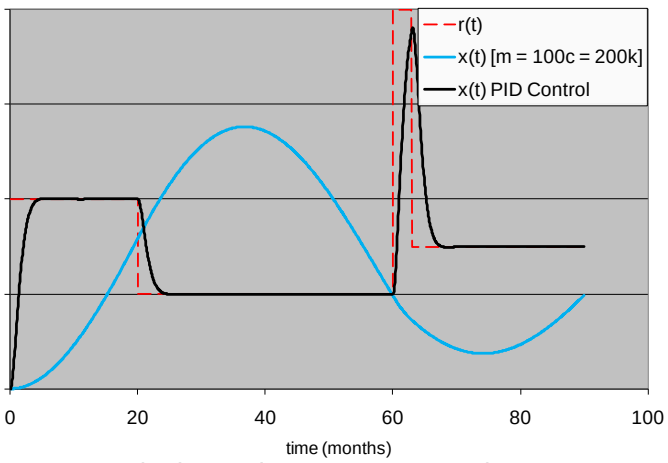
"Resilience: the ability [for the entity] to recover from or adjust to misfortune, damage [to itself], ... " (Alberts & Hayes, 2003). In this context, resilience is the ability to continue to respond to the required GM Approach even when damage causes one or more of the organizational forces to

dominate. For example, a power outage may cause all computer servers to fail and thus the Resisting Force dominates which greatly resists the entity from distributing information broadly.

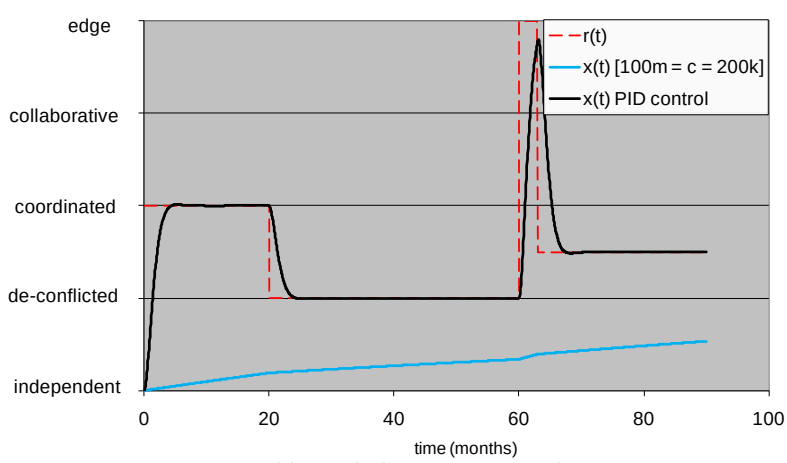
"Damage"	Equation	Response	With Feedback
Change in Momentum dominates	$k\,r \approx m\,\ddot{x}$	Unstable Quadratic	Stable Figure 10a
Resisting Force dominates	$k\,r \approx c\,\dot{x}$	Unstable Linear	Stable Figure 10b
Restoring Force dominates	$k\,r \approx k\,x$	Stable Oscillations	Stable Figure 10c
Change in Momentum and Resisting Force dominate	$k\,r \approx m\,\ddot{x} + c\,\dot{x}$	Unstable Exponential	Stable Figure 10d
Change in Momentum and Restoring Forces dominate	$k\,r \approx m\,\ddot{x} + k\,x$	Meta-stable Sinusoidal	Stable Figure 10e
Resisting and Restoring Forces dominate	$k\,r \approx c\,\dot{x} + k\,x$	Stable Suboptimal	Stable Figure 10f

Table 2: Damage caused by one or more Forces Dominating

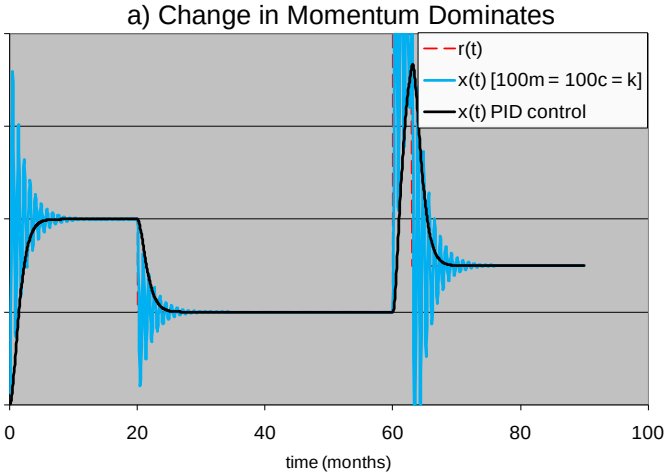
Six "damaged" states exist for a motion system (see Table 2). These damaged systems are not resilient by themselves but compensatory methods provide resilience (stabilization and tracking the required GM approach) in the face of such extreme damage as shown in Figure 10.



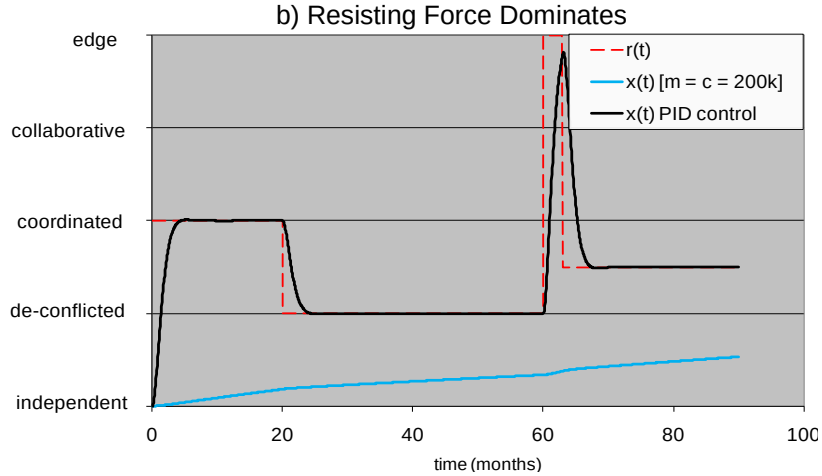
a) Change in Momentum Dominates



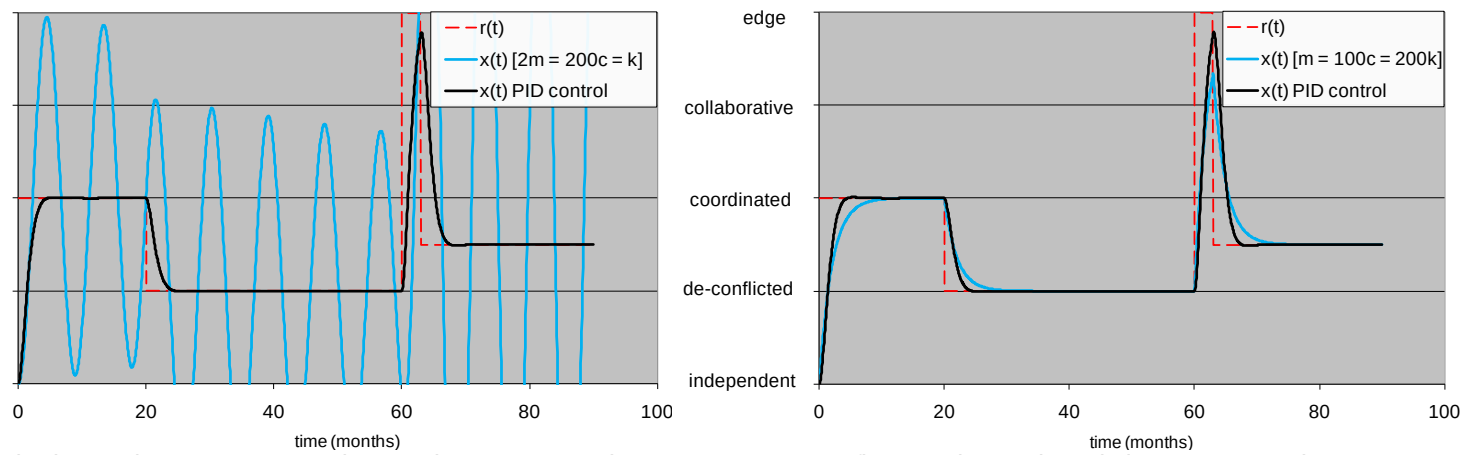
b) Resisting Force Dominates



c) Restoring Force Dominates



d) Change in Momentum and Resisting Force Dominate



e) Change in Momentum and Restoring Force Dominate

f) Restoring and Resisting Force Dominate

Figure 10: Response to "damage to self" without and with PID Control (Resilience)

Disturbance Rejection

The resilience definition also includes "the ability [for the entity] to recover from or adjust to… a destabilizing perturbation in the environment" (Alberts & Hayes, 2003). This destabilizing perturbation in the environment is an <u>external</u> disturbance that causes changes in situation complexity. This external disturbance, in fact, determines the required GM Approach, r(t).

At the same time, one could argue that there are <u>internal</u> disturbances, d(t), related to GM Approach transitions such as internal policies that prevent broader ADR, unexpected acquisition of new information systems that enable seamless distribution of all document types[12], or a dishonest incident leading to mistrust and overly-constrained Patterns of Interaction.

PID control is a well-documented method for known and unknown disturbance rejection, which includes disturbances due to variable uncertainty (Van de Vegte, 1990). Figure 11 shows the response of x(t) to an internal disturbance, d(t), with and without feedback. Note that the functional form of the GM Approach space disturbance is not needed to use PID control.

The simulation results show that without feedback, the GM Approach seems to track the disturbance with a significant offset. Between $0 < t < 20$, x(t) rises above edge due to a high disturbance (perhaps due to the new information system), even though only coordinated GM Approach is required. This initial offset seems to persist for the duration of the scenario; almost as if the entity does has no idea that the disturbance is impacting their tracking performance. With feedback however, the entity monitors both the required GM Approach and the disturbance, and a PID control method provides disturbance rejection: that is, x(t) tracks r(t).

Anticipatory Method

Unlike PID control, Anticipatory methods require a model of the environment (in this case, the GM Approach space). High fidelity models of the environment yield better anticipation and better control. For example, it may be anticipated that the information system maintenance occurs monthly and is unavailable for use over that weekend. The entity might anticipate and

[12] Disturbances can be both constructive and destructive in reaching the required GM Approach position.

compensate for the maintenance schedule by incorporating a backup system, or distribute the information before the weekend. Anticipatory control methods work poorly as model fidelity deteriorates, and must be used in conjunction with disturbance rejection methods (Farrell, 1992).

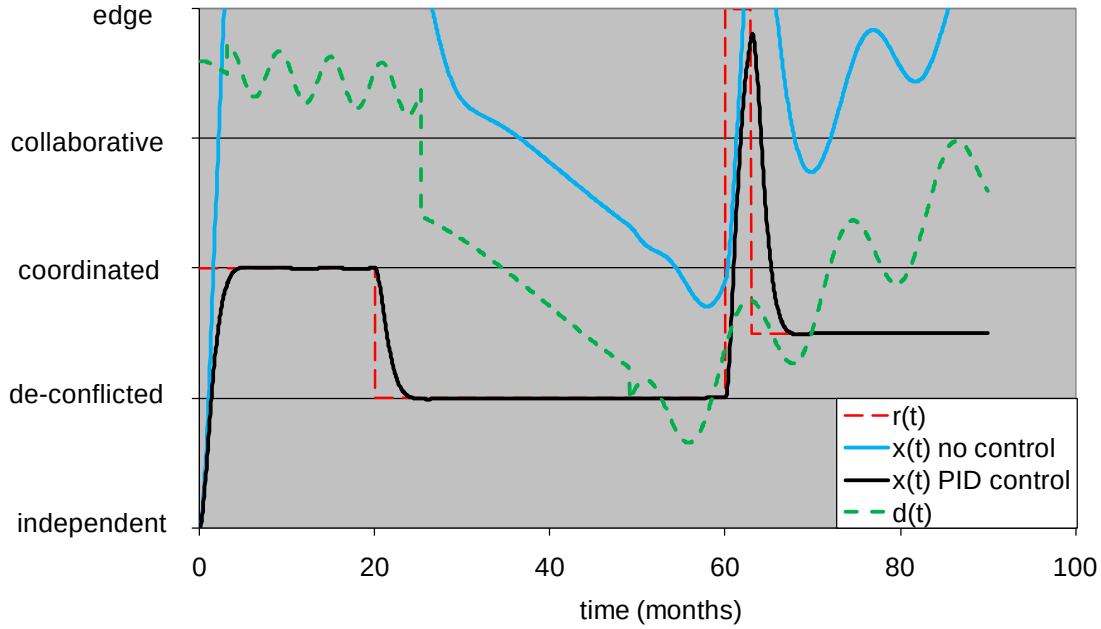


Figure 11: Response to disturbance without and with PID control (disturbance rejection)

As an aside, militaries conduct mission analysis before conducting a major combat operation. This intense activity aims to collect information on strategic objectives, available resources, adversarial intent and resources, as well as political, military, economic, social, information, and infrastructure aspects of the environment. In effect, they are building a model of the mission space. As they build this model they plan and conduct "what-if" scenarios to anticipate the adversary's reaction (red teaming). The better the model, the more confidence they would have in their action-reaction predictions.

Nevertheless, they do not rely solely on the mission analysis results because there are too many unknowns and no plan survives first contact, rather they close the loop by executing the plan, assessing outcomes (feedback), and they make decisions to re-plan if the endstate has not been achieved, or end the mission if the objectives are reached. Military operations are a classical goal-tracking problem solved using anticipation in conjunction with feedback (Farrell, 2007).

Figure 12 shows the open loop response (i.e., no feedback) to an anticipated disturbance (green) with (black) and without (blue) anticipation. Without anticipation, the entity seems to track the disturbance with a significant offset. With anticipation, the entity exactly cancels the known disturbance. If a portion of the disturbance is unanticipated, then the entity must use feedback control to reject the disturbance (not shown but identical to Figure 11).

In terms of responsiveness, anticipatory methods theoretically achieve perfect tracking, x(t) = r(t). If the time to transition from one GM Approach to another (T_t), can be anticipated, then the entity may begin the transition T_t months before r(t) changes. Of course this would mean that r(t) and situation complexity would need to be predicted as well. For a major conflict or natural

disasters, this may not be possible. However, most major sporting events or political summits have start and end dates determined years in advance.

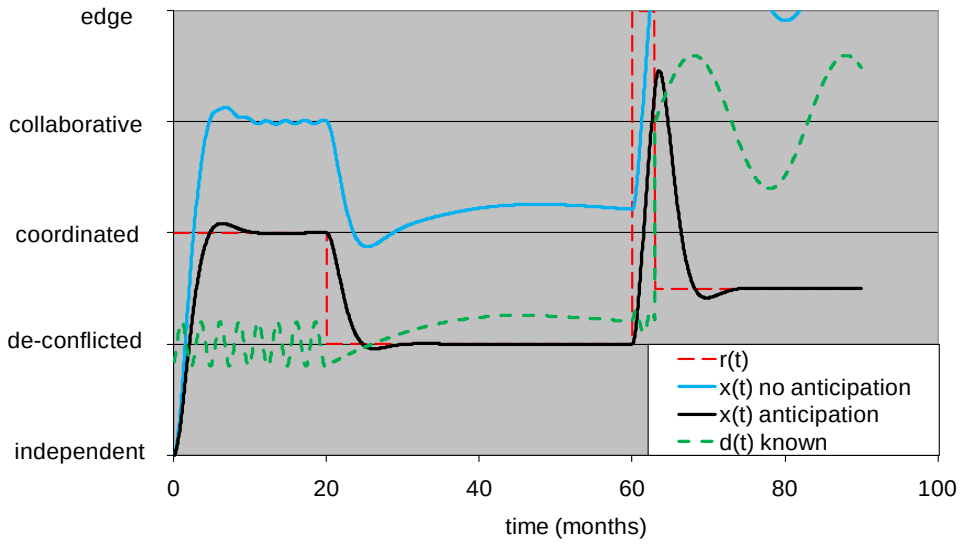


Figure 12: Response to known disturbances with and without anticipation

In terms of robustness and stability, anticipation works best with high fidelity models of the environment are available. However, generating these models is expensive. Anticipation with no feedback is likely to cause instability particularly with low fidelity models. Anticipatory methods must work in concert with compensatory methods to ensure robustness. Anticipatory methods are not applicable for resilience. The entity must be prepared to react to a destabilizing perturbation using compensatory methods.

This model and simulation can predict transition times, which would be useful for making strategic decisions and investments in advance of the event. However, timing is critical: too far in advance and policies and technologies for the anticipated GM Approach may become outdated and expensive to maintain. Too close to the event and the collective may miss the window of opportunity to move to the appropriate GM Approach.

Adaptive Methods

Adaptive control methods have a very specific meaning within the discipline of nonlinear control systems (Slotine & Li, 1991): that is the control gains adapt over time. For example, if K_p adapts or changes as a function of error, then the nonlinear gain can be very large when the error is large producing very fast rise times, and it would be very small when the error is small avoiding overshoot. For illustrative purposes, a nonlinear gain is simulated, $\mathbf{K_{adaptive} = K_p^2 |e(t)|}$. On its own, this gain function produces oscillations (not shown). However, combined with D control, the oscillations are damped out. The response to PD Adaptive control is compared to PD control in Figure 13. The resultant x(t) almost completely overlaps r(t).

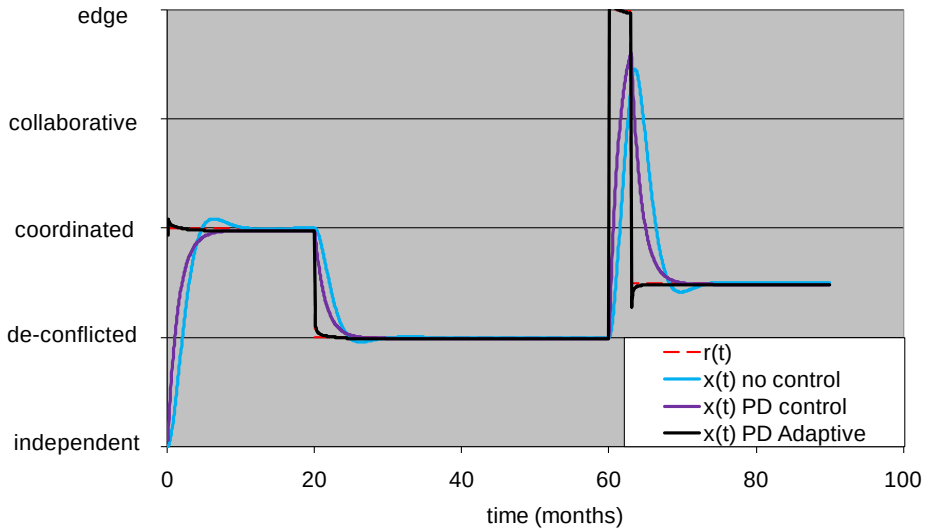


Figure 13: PD Adaptive control compared to PD control and no control responses.

With PD Adaptive control, the effectiveness increases from 80% (no control) to 98% (PD Adaptive) compared to a "no control" response, but the efficiency drops from 80% (no control) to 70% (PD Adaptive) because this type of control is expensive[13]. The strategic investment question is, "is a 18% increase in effectiveness worth a 10% drop in efficiency?" We begin to see how this simulation can be used to make decisions on which method(s) should the collective invest in.

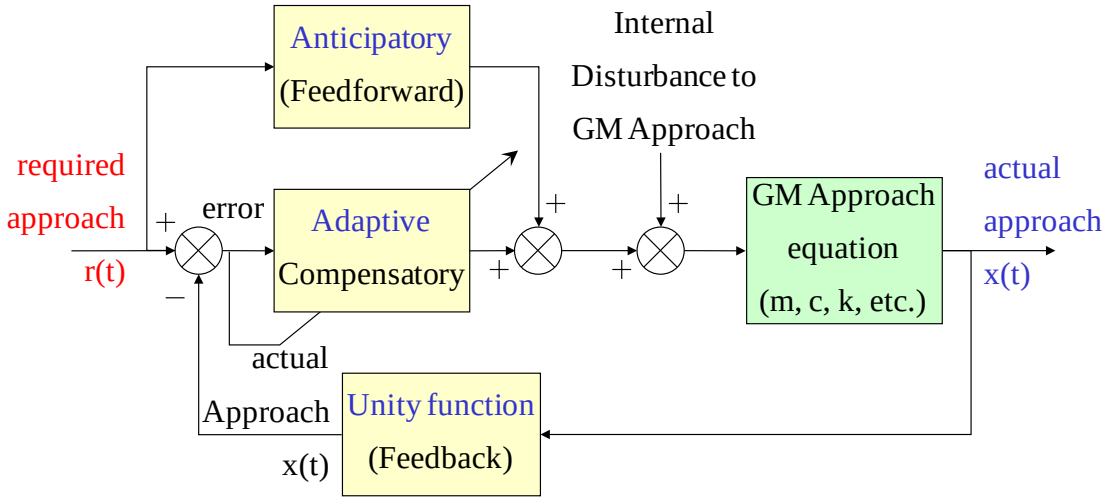


Figure 14: Compensatory, Anticipatory, and Adaptive control methods as part of a control system.

Learning Methods

Figure 14 shows the relationships between the three control methods within a feedback loop, which can be applied during the transition from one approach to another. However, the learning method does not appear in this figure because it is done typically between events (see Figure 15) with representative cases with a limited scenario or vignette. It may take the form of education,

[13] See sections on transition effectiveness and efficiency for how the percentages are calculated.

training, or mission rehearsal. Learning is a process of direct parameter optimization and finding the right balance of m, c, and k that maximizes effectiveness and efficiency. Learning is similar to adaptive methods in that parameters values are modified over time.

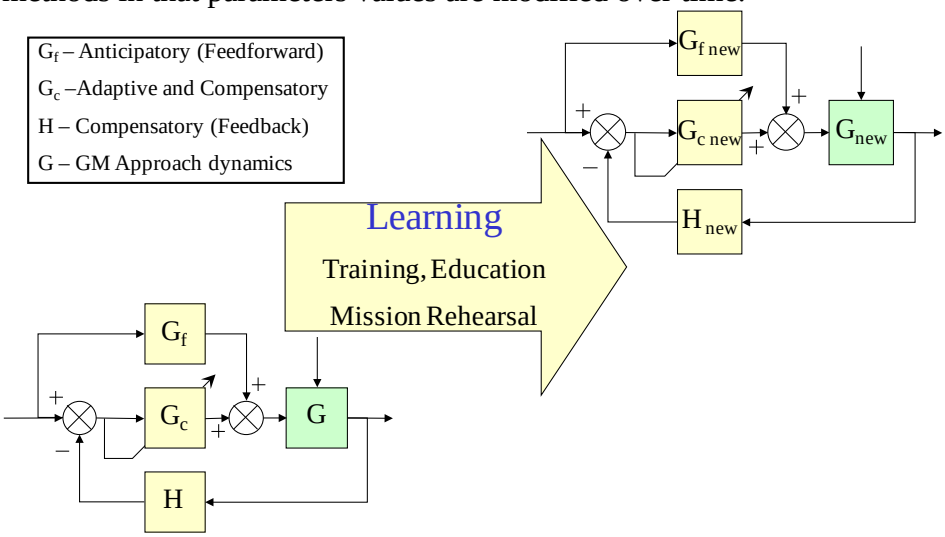


Figure 15: Learning typically occurs between events.

Learning Methods are well documented for motion tracking problems in robotics (Arimoto, Kawamura, & Miyazaki, 1984; Arimoto, Kawamura, Miyazaki, & Tamaki, 1985). Their algorithms are implemented in the simulation to demonstrate the dramatic increase in effectiveness as shown in Figure 16. The first 10 months, going from independent to coordinated, are trained as a small vignette. After the fifth trial, there is no transient response. The entity may go into the operation instantly ready to employ a Coordinated GM Approach.

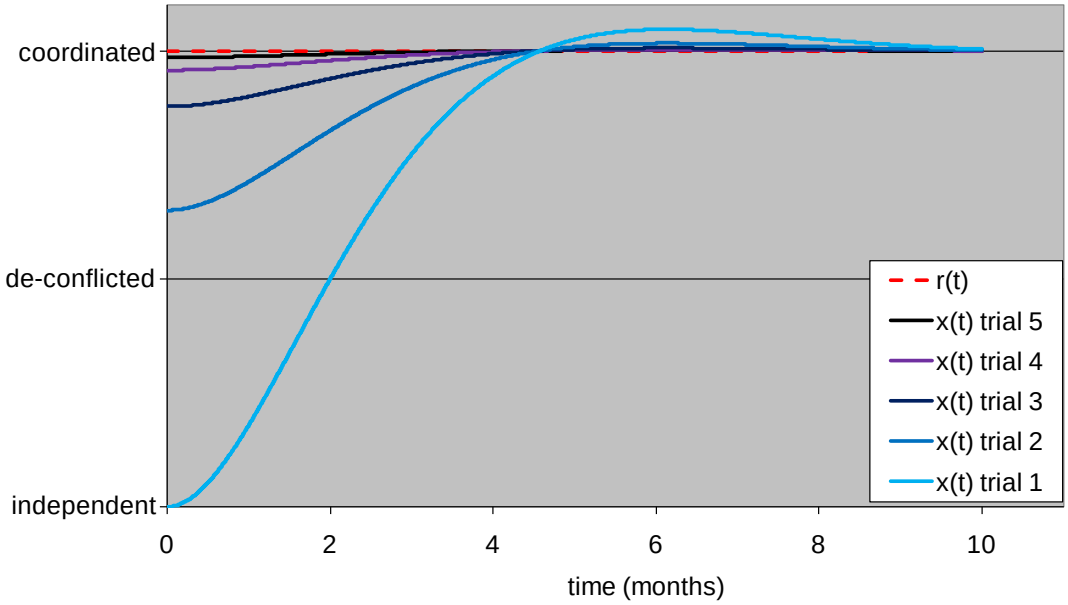


Figure 16: Independent to Coordinated GM Approach Transition Training vignette converges after 5 trials.

Robustness is not guaranteed over the entire space with learning only, since it takes place typically with a limited number of vignettes. However, learning the methods themselves lends

itself to robustness. The governing equation parameters m, c, and k are modified through practice so to improve responsiveness to a representative set of GM approach transitions. If the open loop response is optimized then less effort is needed from the "online" methods, thus increasing overall efficiency. Finally, learning does have an impact on resilience in that the entity may practice their contingency plans if damage to self were to occur.

GM Approach Transition Effectiveness and Efficiency

Effectiveness and efficiency are ubiquitous metrics applied to every state and variable within a complex endeavour: mission effectiveness, planning efficiency, communications effectiveness, and so on. For the purposes of this paper, this discussion is limited to GM Approach transition effectiveness and efficiency.

Effectiveness

In general, effectiveness is a calculation, rather than a measurement, which compares an actual value to a required value (although the actual value is obtained through measurement). The direct effectiveness calculation is the extent to which a state or variable value matches its required value[14] (Farrell, 2005). For ratio and interval variables (e.g., position in 3D space) direct effectiveness is expressed as a percentage of the required value. For ordinal and nominal variables (e.g., position in GM Approach space) direct effectiveness ratio is binary either 1 or 0: that is, the entity either reached the required GM Approach or not. GM Approach Transition effectiveness metric is easily developed with the steady state or representative filters based on a binary ratio at every point in time and then averaged. However, the model provides a continuous approximation of the GM Approach space where x(t) and r(t) are ratio variables. Thus, a ratio can be formed as a good approximation of the filtered effectiveness calculation as follows:

$$\mathbf{effectiveness(t)} = \mathbf{100} \times \frac{\mathbf{x(t)}}{\mathbf{r(t)}} \qquad \cdots\ \mathbf{x(t) \le r(t)} \tag{8}$$

$$\mathbf{effectiveness(t)} = \mathbf{100} \times \frac{\mathbf{r_{max(t)} - x(t)}}{\mathbf{r_{max(t)} - r(t)}} \qquad \cdots\ \mathbf{r(t) < x(t) \le r_{max(t)}} \tag{9}$$

Figure 17 shows the effectiveness curves for "no control", no control with "disturbance" and then "PID control" with disturbance (see Figure 11). The first percentage is a time-weighted average of the effectiveness calculated at each point in time. The bracketed percentage is the effectiveness calculation for a steady state filter. "no control" = 92% (80%), no control with "disturbance" = 41% (20%), and "PID control" with disturbance = 95% (81%).

The steady state effectiveness percentage will be lower than the continuous calculation because it does not include the transient response. The effectiveness drops significantly because of the disturbance. Conversely, effectiveness increases significantly when PID control is used to compensate for the disturbance. The simulation is a powerful tool to calculate GM Approach transition effectiveness for a wide variety of GM Approach configurations (various r(t) profiles, control methods, disturbances, filtered responses, etc.).

[14] The required value has other names such as goal, target, desired state, reference value, end state, objective, etc.

For nominal data that cannot be ordered, effectiveness can still be "calculated" as a logical sum of the effectiveness of lower level variables. This is called an indirect effectiveness calculation. For instance, the indirect effectiveness of transitioning from one GM Approach to another may be the sum the direct effectiveness of ADR, PI, and DI compared to their ideal values or states.

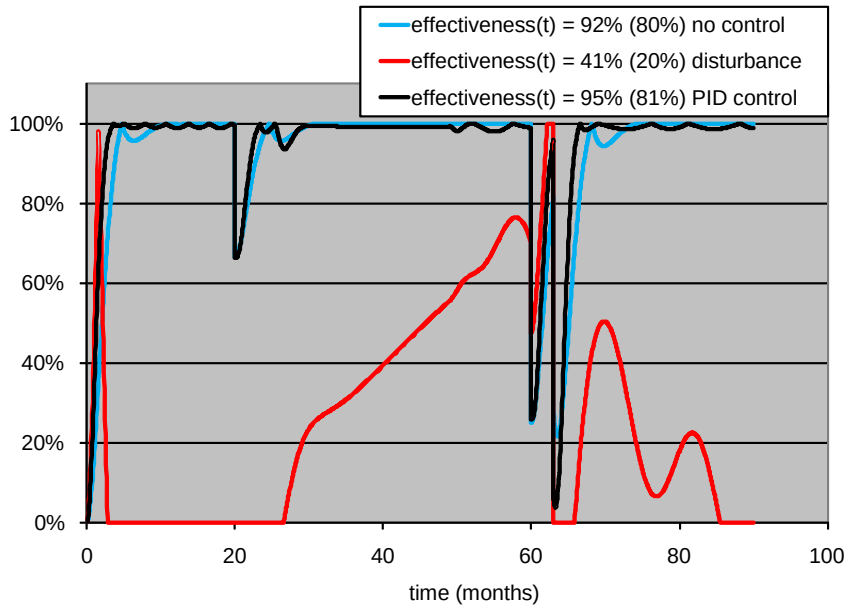


Figure 17: GM Approach transition Effectiveness as a function of time

Efficiency

For mechanical systems, efficiency is the ratio of usable energy out divided by the energy into a system. The analogy for organizational systems is that efficiency is the value or worth of the activity compared to the resources (money, people, etc.) used to accomplish the activity. Both values are difficult to compute. Conceptually, the useful time at steady state divided by the total time could be a surrogate for worth. That is, efficiency can be calculated only when the actual GM Approach reaches the required steady state value. Thus, the steady state filter is used to calculate this time ratio.

The transition cost could be a surrogate for resources, which is assumed to be proportional to the control method used. Learning methods are likely the most expensive, followed by anticipatory, then adaptive, and finally compensatory methods being the least expensive. PID control would be more expensive than PI or PD control, followed by P and "no control" being the least expensive. The transition cost is normalized with respect to the "no control" cost such that the efficiency calculation is always equal to or less than 100% as follows:

$$\textbf{normalized cost} = \frac{\textbf{learning cost} + \textbf{anticipatory cost} + \textbf{adaptive cost} + \textbf{compensatory cost} + \textbf{no}}{\textbf{no control cost}} \tag{9}$$

$$\textbf{efficiency} = 100 \times \left(\frac{\textbf{time at steady state} / \textbf{total time}}{\textbf{normalized cost}} \right) \tag{10}$$

For illustrative purposes, we assume that "PID control" cost is 10% more than the "no control" cost. Thus the corresponding efficiency results for "no control", "disturbances", and "PID control" in Figure 17 is 80%, 3%, and 74% (81% ÷1.1), respectively. Thus, PID control is more effective but less efficient. Thus, strategic decisions can be made with this simulation regarding which methods (behaviours) to invest in, using effectiveness and efficiency as key metrics.

Conclusions

GM Approach agility is the ability to transition from the actual GM Approach to the required GM Approach as the situation complexity level changes over the course of a major event. The model and simulation developed in this paper showed that agility includes all the elements involved in the transition system namely, GM Approach Space and Dimensions, GM Approach laws of motion that yield key entity parameters namely size, stiffness, and resistance, and GM Approach transition methods namely compensatory, anticipatory, adaptive, and learning. The transition system, in turn, produces robustness, responsiveness, resilience, and disturbance rejection. Transition effectiveness and efficiency are key metrics for deciding on which control methods to invest in to get the most agility at the least cost. Figure 18 is a summary of all the relationships discussed in the paper.

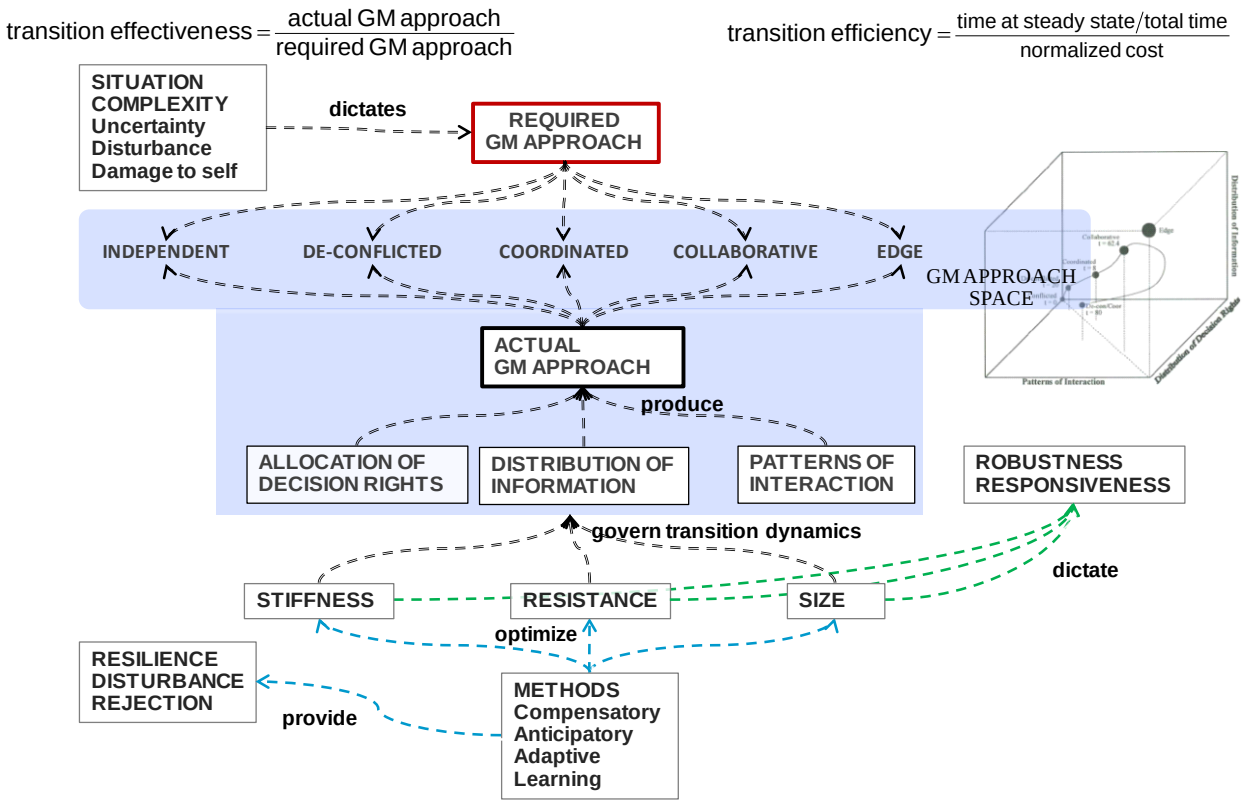


Figure 18: Key parameters and their relationships in the GM Approach transition model

Entity size includes the entity's resources. Entity resistance involves those factors that resist transition from one approach to another such as broken information technology and heavy bureaucracy, culture, tradition, trust and experience. Entity stiffness is related to how

comfortable an entity is with a particular GM approach. Together, these three key parameters determine the damping ratio and natural frequency which in turn dictate the stability, robustness, and responsiveness of the transition system.
Transition methods (entity behaviours) were introduced from Control Theory as a means to drive the actual GM Approach to the required GM Approach. Compensatory methods provide resilience and disturbance rejection, and are arguably the simplest and least expensive to use. They also stabilize unstable systems and improve responsiveness. Anticipatory methods anticipate known disturbances and can act just before the onset of the required approach. Adaptive methods provide near-perfect tracking of the required GM Approach but are costly. Learning methods optimize the system parameters typically between events, and are likely the most expensive.

GM Approach transition effectiveness was defined as a ratio between the actual and required GM Approaches, while efficiency was defined as the steady state time normalized with the total time divided by the transition cost normalized with respect to the "no control" cost. Both effectiveness and efficiency varied depending on the control method employed. The model and simulation becomes a powerful way of understanding and visualizing the transition between approaches and, when validated, may be a useful decision-making tool for strategic investments.

The next step is to evaluate the model using real world data. Work is underway to look for evidence of agility (and the concepts instantiated in this model) for major sporting events. This will be the theme for the final paper on Organizational Agility.

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Annex A
Required GM Approach profile used for Simulation Runs, r(t).

The following is an excerpt from (Farrell & Connell, 2010).
The transition from one C2 approach to another can be traced in the C2 approach space. Figure 2 shows a notional trajectory in the C2 approach space that represents the C2 approach position at various times throughout the complex endeavour. For illustrative purposes, consider the time units to be in months. At the beginning of the endeavour (t = 0), organizations bring their own version of governance and management to complex endeavour and conflicts arise. It quickly becomes obvious that some type of interaction coordination is needed. Sometime later (t > 8) coordination exists, business rules are developed and agreed upon, and areas of responsibility and interest are established. At t = 20 months, the situation is stable and each entity works effectively within its designated area of responsibility. The collective adopts a De-conflicted approach to governance and management (note that the trajectory retraces itself).

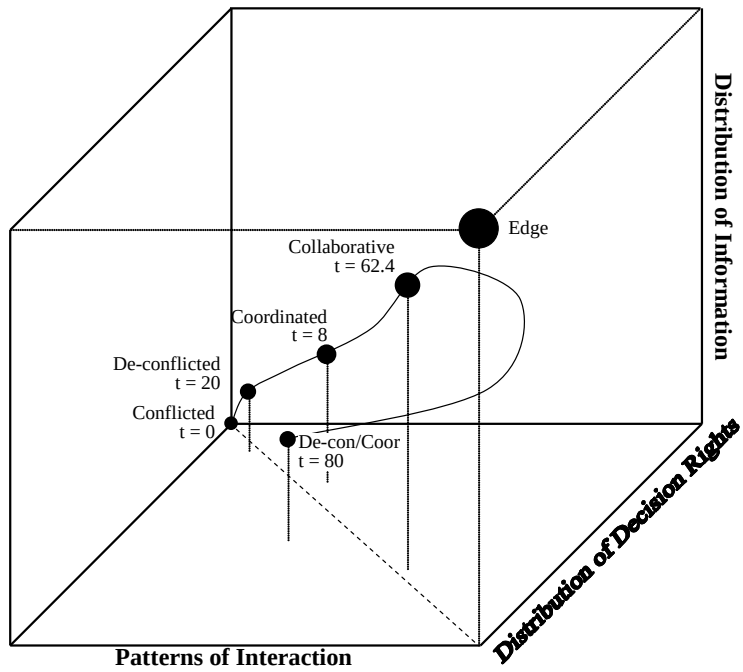


Figure 2: Notional Trajectory within the GM approach space

Five years from the start (t =60, not displayed) an unanticipated catastrophic event significantly increases the overall complexity and a De-conflicted approach no longer works. The collective must dynamically re-assess the governance and management structures to the point where ADR and DI are very broad and PI is unconstrained and the collective passes through a Collaborative approach a few months later (t = 62.4) but the trajectory never quite reaches the required Edge approach. Three months later (t = 63 not displayed), the event subsides and the GM approach settles somewhere between De-conflicted and Coordinated (t > 80). This fictitious vignette illustrates explicitly the SAS-065 Organizational Agility definition. However, it has elements of Kaplan's definition by the collective possessing multiple GM approaches, Alberts and Hayes' definition by the collective being responsive and flexible, and Spaans et al's definition by the collective having an adaptive stance and choosing appropriate approaches as the situation changes. *This notional scenario is mocked up in the simulation as r(t).*

Annex B
Other Theories applied to Motion Tracking Problems

Control Theory is not the only paradigm one might consider. The following paragraphs present some of the pros and cons of other paradigms that could be used for this model.

Stimulus-Response
A Stimulus-Response paradigm (Skinner and Watson in (Meyers, 1989)) pre-supposes that for every possible required GM Approach profile (stimulus) there is a corresponding response that is stored the equivalent of a corporate memory, and retrieved as needed. For complex situations, there would be endless required profile permutations and a number of those that will not be known a priori. A stimulus-response paradigm has no means of dealing with uncertainty or unknown disturbances common in highly complex situations. Stimulus-response is open-loop control with no way of ensuring stability. However, a clear advantage of stimulus-response is potentially very fast.

Anticipatory behaviour on its own is a type of stimulus-response where the stimulus is an internal mental model of the situation. The advantage of this paradigm is that responses are seemingly instantaneous if the timing is right. The disadvantage is that poor implementation of anticipation may cause unrecoverable instabilities. If the child anticipates that their parent is going to the toy store and confidently struts in that direction without looking back (i.e., feedback) and the parent changes their mind and goes to a clothing store at the opposite end of the mall, then anticipatory behaviour without feedback would cause the separation distance to grow.

Ecological Psychology
Gibson and others would suggest Ecological Psychology (Gibson, 1979) where the environment shapes human behaviour. For example, a mall built as a three-story spiral that has one single corridor constrains movement to forwards and backwards thus reducing the opportunities for children to be separated from their parents. This mall design also affords potential costumers passing by a majority of stores, compared to a traditional three-story mall design with multiple corridors intersecting at right angles. Complex environments have so many constraints (obstructions, uncertainty, disturbances) that humans often cannot see the affordances and tend to do nothing if there is no safe path. Interestingly, as an entity grows and matures they may view constraints as affordances or opportunities for success.

1st and 3rd Laws of Motion
If the GM Approach space obeys an equivalent Newtonian 2nd law of motion, is there an equivalent for the 1st and 3rd law of motion?

Newton's first law of motion states that an object at rest remains at rest, and an object in motion remains in motion. This is a theoretical axiom where the closest real example would be an object moving through out space. The equivalent 1st law of motion in the GM Approach space is that an entity at rest at a specific (ADR, DI, PI) position will remain at that position (or at rest), unless a forcing function moves it away from that position, and an entity in motion (i.e., changing their GM Approach) remains in motion, unless opposing forces act to slow it down. However, it is difficult, if not impossible to imagine a case where there are no opposing forces to

slow down the transition, and it continues on past edge. Thus, the equivalent of Newton's 1st law of motion in the GM Approach space is only a theoretical equivalent.

Newton's 3rd law is that for every action there is an equal and opposite reaction. This law applies when two objects are in contact with each other. The situation described in this paper only follows one position in the GM Approach space as it moves through time, x(t). Thus, the 3rd law does not apply.

Annex C
Computer Code for GM Approach Transition Model and Simulation

The following pages archive one of the later versions of the computer code used to build the simulation. The code itself was developed in an iterative fashion. That is, the conceptual model dictated the simulation, and the simulation results help to refine the model. The programming language used was Visual Basic in Excel 2007. Solving the differential equations was done using simple numerical methods, which come with sampling time challenges. However, these challenges were avoided by keeping the integration interval at 0.0001 seconds.

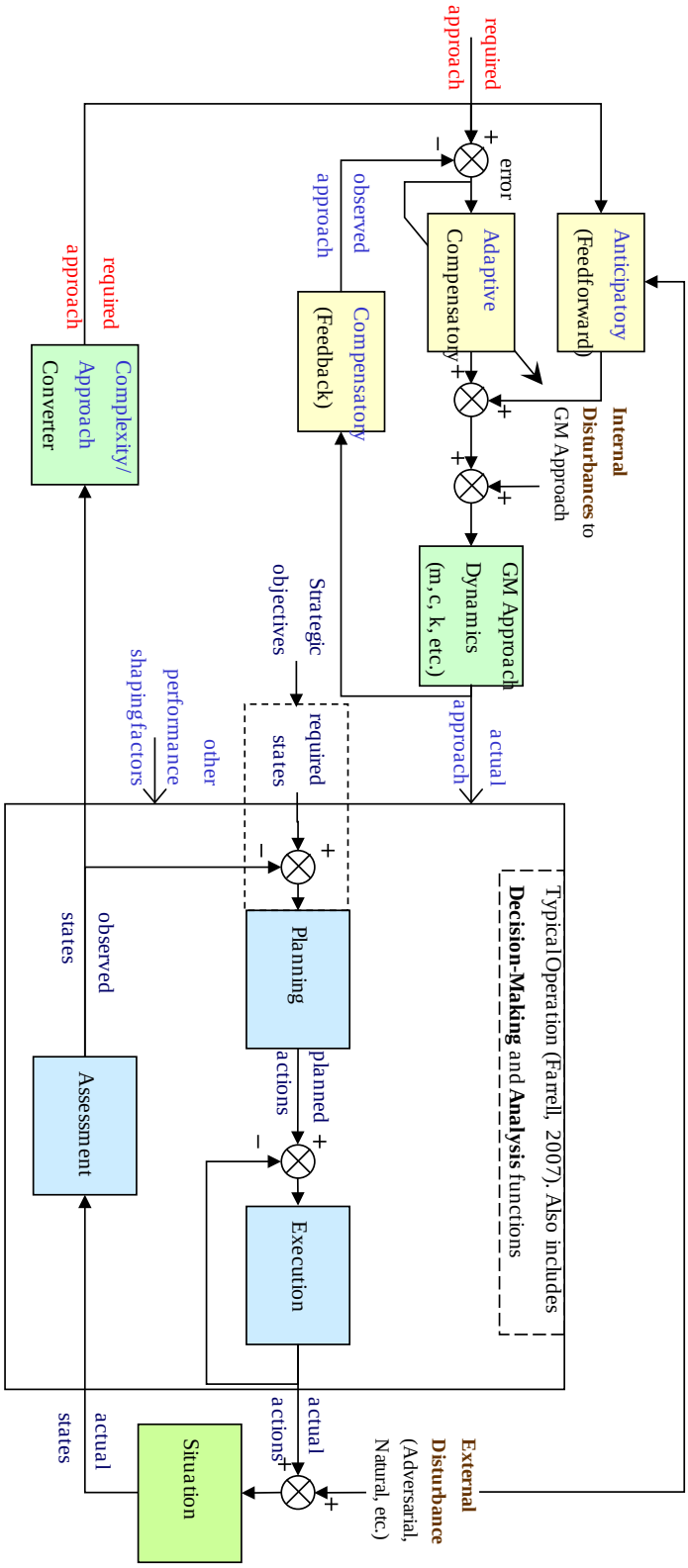
```
Dim t As Single 'time
Dim dt As Double 'time step
Dim pt As Single 'print time interval
Dim delay As Single, switch As Integer, disturbance As Double 'feedforward time delay and anticipatory
switch and resultant disturbance
Dim starttime As Single, stoptime As Single 'start and stop time for simulation
Dim rt(5) As Single, A(4) As Single, B(4) As Single, D(4) As Single, w(4) As Single, ph(4) As Single
'parameter values for reference
Dim rtd(5) As Single, Ad(4) As Single, Bd(4) As Single, Dd(4) As Single, wd(4) As Single, phd(4) As Single
'parameter values for unknown disturbances
Dim frt(5) As Single, Af(4) As Single, Bf(4) As Single, Df(4) As Single, wf(4) As Single, phf(4) As Single
'parameter values for known disturbances
Dim rn As Double, rn1 As Double, rn2 As Double, rn3 As Double 'n, n-1, n-2, n-3 r values (reference)
Dim fn As Double, fn1 As Double ', fn2 As Double, fn3 As Double n, n-1, n-2, n-3 f values (feedforward)
Dim dn As Double, dn1 As Double ', dn2 As Double, dn3 As Double n, n-1, n-2, n-3 d values (disturbance)
Dim un As Double, un1 As Double, un2 As Double, un3 As Double 'n, n-1, n-2, n-3 u values
Dim xn As Double, xn1 As Double, xn2 As Double, xn3 As Double 'n, n-1, n-2, n-3 x values
Dim xfilter As Double, toler As Double 'converts continuous to discrete profile, toler sets closeness
values
Dim filter As String, stay As String 'flag for filter type, and flag for steady state filter
Dim en As Double, en1 As Double, en2 As Double, en3 As Double 'n, n-1, n-2, n-3 e values
Dim m As Single, c As Single, k As Single 'organizational size, resistance to change, flexibility
Dim c1 As Single, c2 As Single, c3 As Single, c4 As Single 'derived constants
Dim wn As Single, z As Single 'organizational natural frequency and damping ratio
Dim Kp As Single, Ki As Single, Kd As Single 'Proportional, Integral, Derivative controller gains
Dim Gp As Single, Gi As Single, Gd As Single 'Proportional, Integral, Derivative controller constant gains
Dim lower As Double, upper As Double 'lower and upper bounds of the random function generator for the
disturbance
Dim differ As String, compensatory As String, feedfoward As String, adaptive As String 'integration
method, on/off compensatory, feedforward, and adaptive switches
Dim gain As Double 'gain for adaptive
Dim knowndisturbance As String, unknowndisturbance As String 'these values turn on and off the disturbance
calculation
Dim pii As Double '3.14159265358979
Dim j As Long, i As Integer, f As Integer 'counter for print time interval, reference  values, feedforward
values

Sub integrate()
'remove old numbers and print out headers
Worksheets("Sheet1").Range("H:M").Value = ""
Worksheets("Sheet1").Range("H" & 1).Value = "time"
Worksheets("Sheet1").Range("I" & 1).Value = "r(t)"
Worksheets("Sheet1").Range("J" & 1).Value = "x(t)"
Worksheets("Sheet1").Range("K" & 1).Value = "d(t)"
Worksheets("Sheet1").Range("L" & 1).Value = "x(t) filtered"
Worksheets("Sheet1").Range("M" & 1).Value = "xneff"

'get reference parameters
i = 1
pii = 3.14159265358979
Do While i <= 4
```

```
    rt(i) = Worksheets("Sheet1").Range("A" & 16 + i).Value
    A(i) = Worksheets("Sheet1").Range("B" & 16 + i).Value
    B(i) = Worksheets("Sheet1").Range("C" & 16 + i).Value
    D(i) = Worksheets("Sheet1").Range("D" & 16 + i).Value
    w(i) = Worksheets("Sheet1").Range("E" & 16 + i).Value * 2 * pii
    ph(i) = Worksheets("Sheet1").Range("F" & 16 + i).Value * pii / 180
    frt(i) = Worksheets("Sheet1").Range("A" & 37 + i).Value
    Af(i) = Worksheets("Sheet1").Range("B" & 37 + i).Value
    Bf(i) = Worksheets("Sheet1").Range("C" & 37 + i).Value
    Df(i) = Worksheets("Sheet1").Range("D" & 37 + i).Value
    wf(i) = Worksheets("Sheet1").Range("E" & 37 + i).Value * 2 * pii
    phf(i) = Worksheets("Sheet1").Range("F" & 37 + i).Value * pii / 180
    rtd(i) = Worksheets("Sheet1").Range("A" & 47 + i).Value
    Ad(i) = Worksheets("Sheet1").Range("B" & 47 + i).Value
    Bd(i) = Worksheets("Sheet1").Range("C" & 47 + i).Value
    Dd(i) = Worksheets("Sheet1").Range("D" & 47 + i).Value
    wd(i) = Worksheets("Sheet1").Range("E" & 47 + i).Value * 2 * pii
    phd(i) = Worksheets("Sheet1").Range("F" & 47 + i).Value * pii / 180

    i = i + 1
Loop

'get time variables, integration method, controller gains, and organizational attributes
m = Worksheets("Sheet1").Range("B4").Value
c = Worksheets("Sheet1").Range("B5").Value
k = Worksheets("Sheet1").Range("B6").Value
dt = Worksheets("Sheet1").Range("B22").Value
starttime = Worksheets("Sheet1").Range("B23").Value
stoptime = Worksheets("Sheet1").Range("B24").Value
pt = Worksheets("Sheet1").Range("B25").Value
differ = Worksheets("Sheet1").Range("B26").Value
adaptive = Worksheets("Sheet1").Range("B8").Value
gain = Worksheets("Sheet1").Range("C9").Value
compensatory = Worksheets("Sheet1").Range("B9").Value
knowndisturbance = Worksheets("Sheet1").Range("F36").Value
unknowndisturbance = Worksheets("Sheet1").Range("F46").Value
feedforward = Worksheets("Sheet1").Range("B13").Value
Gp = Worksheets("Sheet1").Range("B10").Value
Gi = Worksheets("Sheet1").Range("B11").Value
Gd = Worksheets("Sheet1").Range("B12").Value
delay = Worksheets("Sheet1").Range("C13").Value
rt(5) = stoptime + dt 'rt(5) must be defined in terms of stoptime
frt(5) = stoptime + dt 'frt(5) must be defined in terms of stoptime
rtd(5) = stoptime + dt 'rtd(5) must be defined in terms of stoptime
lower = Worksheets("Sheet1").Range("B44").Value
upper = Worksheets("Sheet1").Range("C44").Value
toler = Worksheets("Sheet1").Range("E4").Value
filter = Worksheets("Sheet1").Range("E5").Value

'set initial values, constants, and counters
xn = Worksheets("Sheet1").Range("B27").Value
xn1 = xn: xn2 = xn: xn3 = xn: xfilter = xn
un1 = 0: un2 = 0
fn = 0: fn1 = fn
dn = 0: dn1 = dn
stay = "off"
If (k <> 0) Or (m <> 0) Then
    If k <> 0 Then
        If m <> 0 Then
            wn = (k / m) ^ 0.5
            z = (c / m / 2 / wn)
        Else
            If c = 0 Then
                differ = "no resisting force or size"
            Else
                wn = k / c
                z = 1
                differ = "no size"
            End If
```

```
        End If
        c1 = 1 - 2 * z * wn * dt
        c2 = (wn * dt) ^ 2
    Else
        c3 = 1 - 2 * c / m * dt
        c4 = dt ^ 2
        differ = "no restoring force"
    End If
Else
    differ = "no restoring force or size"
End If

i = 0: j = 1: f = 1
t = starttime
If feedforward = "off" Then switch = 1 Else switch = 0

Worksheets("Sheet1").Range("B14").Value = switch

Do Until t > stoptime
    'update reference and disturbance counter
    If t >= rt(i + 1) Then
        i = i + 1
    End If

    'calculate r(n)
    rn3 = A(i) + B(i) * (t - rt(i) - 3 * dt) + D(i) * Sin(w(i) * (t - rt(i) - 3 * dt) + ph(i))
    rn2 = A(i) + B(i) * (t - rt(i) - 2 * dt) + D(i) * Sin(w(i) * (t - rt(i) - 2 * dt) + ph(i))
    rn1 = A(i) + B(i) * (t - rt(i) - dt) + D(i) * Sin(w(i) * (t - rt(i) - dt) + ph(i))
     rn = A(i) + B(i) * (t - rt(i)) + D(i) * Sin(w(i) * (t - rt(i)) + ph(i))

    'update feedforward counter
    If t >= (rtd(f + 1) + delay) Then
        f = f + 1
    End If

    'calculate f(n) known disturbance, rectified time delayed
    Select Case knowndisturbance
    Case "off"
        fn = 0
    Case "on"
        If t < delay Then
          fn1 = 0: fn = 0
        Else
          fn1 = Af(i) + Bf(i) * (t - frt(i) - dt) + Df(i) * Sin(wf(i) * (t - frt(i) - dt) + phf(i))
           fn = Af(i) + Bf(i) * (t - frt(i)) + Df(i) * Sin(wf(i) * (t - frt(i)) + phf(i))
        End If
        If fn > 2 Then fn = 2 'these two lines of code should not be needed if this disturbance is known!
        If fn < 0 Then fn = 0
    End Select

    'calculate d(n) unknown disturbance
    Select Case unknowndisturbance
    Case "off"
        dn1 = 0: dn = 0
    Case "on"
        dn1 = dn
         dn = Ad(f) + Bd(f) * (t - rtd(f)) + Dd(f) * Sin(wd(f) * (t - rtd(f)) + phd(f)) + (upper - lower)
* Rnd + lower
        If dn > 2 Then dn = 2
        If dn < 0 Then dn = 0
    End Select

    disturbance = dn1 + fn1 * switch
    If disturbance > 2 Then disturbance = 2 - (disturbance - 2) / 2
    If disturbance < 0 Then disturbance = -(disturbance - 0) / 2

     'calculate e(n)
    en3 = rn3 - xn3: en2 = rn2 - xn2: en1 = rn1 - xn1: en = rn - xn
```

```
'calculate u(n-1)
    Select Case compensatory
    Case "off"
        un1 = rn1
    Case "P"
          un1 = Kp * en1 '+ un2 - Kp * en2
    Case "PI"
        un1 = un2 + Kp * (en1 - en2) + 0.5 * Ki * (en1 + en2) * dt
    Case "PD"
        un1 = Kp * en1 + Kd * (en1 - en2) / dt
    Case "PD Adaptive"
        un1 = Kp * Kp * Abs(en1) * en1 + Kd * (en1 - en2) / dt 'Kp Adaptive
    Case "PID"
        un1 = un2 + Kp * (en1 - en2) + 0.5 * Ki * (en1 + en2) * dt + Kd * (en1 - 2 * en2 + en3) / dt
    End Select

    'calculate the nth value for x(t) GM Approach over time
    Select Case differ
    Case "backwards"
        xn = xn1 + c1 * (xn1 - xn2) + c2 * (un1 + disturbance - xn1) 'backwards difference
    Case "central"
    xn = xn2 + c1 * (xn1 - xn3) + 2 * c2 * (un1 + disturbance - xn1) 'central difference
    Case "no restoring force"
        xn = xn1 + c3 * (xn1 - xn2) + c4 * (un1 + disturbance) 'backwards difference
    Case "no size"
        xn = xn1 + k / c * dt * (un1 + disturbance - xn1) 'backwards difference
    Case "no restoring force or size"
        xn = xn1 + dt / c * (un1 + disturbance) 'backwards difference
    Case "no resisting force or size"
        xn = un1 + disturbance 'backwards difference
    End Select

    un2 = un1
    xn3 = xn2: xn2 = xn1: xn1 = xn

    'Map continuous GM Approach to the GM Approach Space regions.
    Select Case filter
    Case "representative"
        'note that xn represents the magnitude of a vector originating from the origin to
        'a point in the GM Approach space.  xfilter represents the centroid of each of the five
        'cubes within the space.
        If xn < 0.01 Then
            xfilter = 0.001 'conflicted GM Approach
        ElseIf (xn > 0.01) And (xn < 0.1) Then
            xfilter = (0.1 - 0.01) / 2 'this is part of the space that does not exist
        ElseIf (xn >= 0.1) And (xn < 0.5 + 0.25) Then
            xfilter = 0.5 'de-conflicted GM Approach
        ElseIf (xn >= 1 - 0.25) And (xn < 1 + 0.25) Then
            xfilter = 1 'co-ordinated GM Approach
        ElseIf (xn >= 1.5 - 0.25) And (xn < 1.5 + 0.1) Then
            xfilter = 1.5 'collaborative GM Approach
        ElseIf (xn >= 1.6) And (xn < 1.9) Then
            xfilter = (1.9 - 1.6) / 2 + 1.6 'this part of the space does not exist.
        ElseIf xn >= 1.9 Then
            xfilter = 2 'edge GM Approach
        End If
    Case "steady state"
        '   This filter assumes it is possible to reach any point between de-conflicted and collaborative
GM approaches
            If xn <= 0.01 Then
                xfilter = 0.001 'independent GM Approach close to zero
        '   ElseIf (xn > 0.01) And (xn < 0.1) Then 'do nothing - this is part of the space that does not
exist
            ElseIf (xn >= 0.1) And (xn < 1.6) Then 'between de-conflicted and collaborative
                If (Abs(rn - xn) <= toler) And (stay = "off") Then 'filter transient response, only output
steady state response
                    xfilter = xn
                    stay = "on"
                ElseIf (Abs(rn - xn) > toler) And (stay = "on") Then
```

```
                    stay = "off"
                End If
        '   ElseIf (xn >= 1.6) And (xn < 1.9) Then 'do nothing - this is part of the space that does not
exist
            ElseIf xn >= 1.9 Then
                xfilter = 2 'edge GM Approach
            End If
    End Select

    'print every pt interval
    If t >= j * pt Then
        Worksheets("Sheet1").Range("H" & j + 1).Value = t
        Worksheets("Sheet1").Range("I" & j + 1).Value = rn
        Worksheets("Sheet1").Range("J" & j + 1).Value = xn
        Worksheets("Sheet1").Range("K" & j + 1).Value = disturbance
        Worksheets("Sheet1").Range("L" & j + 1).Value = xfilter
        If xn > 2 Then xneff = 2 Else xneff = xn
        Worksheets("Sheet1").Range("M" & j + 1).Value = xneff
      j = j + 1
    End If
    t = t + dt
Loop
        Worksheets("Sheet1").Range("e9").Value = en1
End Sub
```

Annex D
GM Approach in context of an Operation

The following diagram shows how GM Approach shapes the operation. It is not part of the main operational loop but it does influence planning, execution, assessment, decision-making, and analysis. Ultimately it impacts the mission effectiveness and efficiency. Note well that r(t) is generated from the states of the environment.