A Collaborative Manufacturing Collective

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Abstract

The extent of collaboration among the companies in a manufacturing network impacts the parametric fluctuations in the network. This is displayed explicitly by the form of the network’s normal modes. By gradually increasing the number of companies that actively collaborate, it is possible to see how the form of the normal modes changes. Initial understanding of this normal mode’s resonant damping was developed using a LOGICS (Learning Object Game Immersed Complex Systems) simulation. A traditional fluctuation-plagued supply chain was transformed into an efficient collaborative manufacturing collective. The improvement is achieved while still honoring the desire of individual companies not to directly share what might be considered proprietary information with another company. The method is extendable and should be applicable to more complex adaptive cloud-coordinated manufacturing networks in which efficiency is obtained by system-wide LOGICS-based feedback to individual companies.

1. Introduction

The method described is designed to accommodate adaptive cloud-controlled manufacturing networks in which efficiency is achieved by cloud-mediated system performance feedback to individual companies. The result should be a collaborative manufacturing collective in which companies behave less randomly and wastefully, by utilizing an interactive “plasma” architecture of coordinated entities whose actions are closely tied to the desired system output.

It is well known that the overall operation of a collection of companies needs to be improved. Companies do not operate in isolation, but are usually strongly dependent on each other. They are tied together in complex networks where the outputs of some companies become the inputs that other companies require to generate their outputs. Many of these networks are comprised of small or medium sized companies that typically lack the resources to respond rationally to changes in the customer demands that companies at the end of the supply chains experience. As a result, the companies often experience wild and wasteful fluctuations in their operational parameters. This is a serious problem for the economy, as small companies comprise a very large portion of an economy’s total number of companies. In the Los Angeles area, for example, the distribution of the number of companies follows a strongly decreasing exponential function of a company’s output [1]. And on a larger scale, of the more than 302,000 exporting companies in the United States, nearly 98 percent (295,594) in 2011 were small or medium sized companies with less than 500 people [2].

To eliminate the undesired wild parametric fluctuations, it would be highly desirable if the individual firms were able to respond rationally to changes in the demand requirements rather than respond intuitively only to local changes in supply and demand. In this way, the system could operate more as an efficient collaborative manufacturing collective.

Unfortunately, a strong barrier to operation as a collaborative manufacturing collective is the reluctance of a company to share information – which can be considered proprietary - directly with another company. Another barrier is the lack of an easy and cost-effective way for an individual company to implement and benefit from rational operational strategies that take into account the overall condition of the collective.

This paper has two primary objectives: The first is to address an important missing underlying ingredient in the understanding of how to operate a group of companies as a collaborative manufacturing collective. The second is to discuss a method by which the collaborative manufacturing collective ideal can be achieved, while still respecting the reluctance of a company to share proprietary information directly with another company.

The basic underlying ingredients of the method have already been addressed in the literature in the form of simulations and of statistical physics approaches.

J.D. Sterman and his colleagues at MIT performed a useful service by providing business schools with a widely used simulation game that demonstrates a beer distribution supply chain [3]. Many variants of the beer game have arisen, including some very recent work, LOGICS, which used gamification techniques [4] to
create an effective learning tool to encourage rational collaboration to solve the game’s inventory optimization problem [5, 6]. The gaming results indicate that the oscillations are due to the overreaction to input fluctuations by the individual entities in the chain, and the results strongly suggest that the situation could be improved by using information technology to provide real-time feedback from an optimal concurrent simulation.

In addition, statistical physics techniques have been applied to provide insight on the nature of the oscillations. The LOGICS approach can be used to encourage gamers to adopt and experiment with other supply chain management techniques such as those described in series of papers by Armbruster et al, that used a continuum model of supply chains based on a thermodynamics perspective with interactions between companies described by a variety of mean field models [7, 8]. Another LOGICS game could be used to encourage the avoidance of convective instabilities discussed by Ouyang and his associates, by agreeing to order commitments [9]. Other LOGICS designs could address and encourage the use of similar instability solutions as suggested by Nagatani et al through the use of various production strategies for stabilization [10].

The initial set of LOGICS designs were designed to encourage gamers to use the Dozier and Chang approach of using information technology to share an optimized system level simulation to reduce the production inventory oscillations [11]. Their previous work had shown that when companies are organized into in daisy chain architectures and influenced by only the companies immediately above and below it in the chain, a sound-wave-like normal mode occurs, whereas when it is influenced by the behavior of all the companies in the chain, the normal mode changes into one resembling more a plasma oscillation. The work has also shown that the form of the normal mode is important for determining the most effective means of damping inventory fluctuations. Specifically, both a linear treatment and a quasilinear extension of the linear treatment of the fluctuations show that optimum control is achieved by resonantly interacting with the normal modes. For the two extremes of nearest neighbor influence and universal influence, the form of the normal modes is known. For practical purposes, however, it is necessary also to know the form of the normal modes when the number of companies over which influence extends is intermediated between the two extremes, i.e. somewhere between the nearest neighbor influence and universal influence.

The first purpose of this paper is to determine how the form of the normal modes morphs from a sound-wave-like form to the plasma oscillation-like form as the number of companies involved in mutual influence is gradually increased. This would allow the evolution of the use of LOGICS to persuade the adoption of more modernistic concurrent production collaboratives. Important investment decisions require knowledge about whether a gradual transition occurs or whether a sudden first order phase transition occurs at some threshold number of collaborating companies. This is treated in Section 2.

The second purpose of the paper is addressed in Section 3. It builds on the results of Section 2 and of the LOGICS learning game [2, 3] referenced earlier to suggest that the use of the Internet cloud to enable traditional supply chain architectures be replaced by modern concurrent collaborative production collectives. The intent of this approach is to eliminate the need for sharing localized proprietary information by creating a system level commitment to an operational rational environment. Section 3 also emphasizes that the approach of this paper is not limited to linear supply chains.

2. Dependence of inventory fluctuations on the extent of rationality sharing

Section 2.1 summarizes the basic normal mode approach, discussing both the statistical physics derivation of a normal mode’s dispersion relation and the importance of resonantly interacting with the normal mode in order to achieve optimum damping and control of unwanted inventory fluctuations.

Section 2.2 presents the primary results, showing the dispersion relations and the corresponding phase and group velocities, for various degrees of collaborative interaction.

Section 2.3 discusses the significance of the results.

2.1 Normal mode modeling approach

Introduce a distribution function \( f(n,v,t) \) for the inventory (i.e. for the number of production units) along the supply chain. It depends on the position \( n \) of a company in the chain, the rate of flow \( v \) of a production unit through each position, and on the time \( t \).

In order to replace difference equations with more familiar differential equations, the position \( n \) of a company in a chain will be considered to be a continuous variable instead of a discrete variable. Dozier and Chang have shown that the modifications resulting from dealing with the discrete label \( n \) instead of the continuous variable \( n \) for long supply chains are
unimportant, the basic features of both treatments being essentially the same [11]. In statistical physics parlance, the variables n and v comprise the phase space for the problem, and f(n,v,t) dn dv denotes the number of production units in the phase space intervals dn and dv at a given n and v at the time t.

From its definition, this distribution function satisfies a conservation equation in the phase space of n and v, if it is assumed that no production units are destroyed at each level of the chain:

$$\frac{\partial f}{\partial t} + \frac{\partial}[fv]{\partial n} + \frac{\partial}[fdv]{\partial v} = 0$$  \hspace{1cm} (1)

This equation simply states that the change of fdnv is due only to the divergence of the flow into the phase space volume dn dv. In a perfectly operating supply chain, we would expect that there would be no divergence in the flow. By permitting a divergence in the flow – i.e., permitting the flow into a volume element dn dv to be different than the flow out, the possible existence of local inventory fluctuations is allowed.

By introducing a thermodynamic force F [1] that influences the velocity v of the production unit, this equation can be rewritten

$$\frac{\partial f}{\partial t} + v \frac{\partial f}{\partial n} + F \frac{\partial f}{\partial v} = 0$$  \hspace{1cm} (2)

Since position n and velocity v of the production unit are independent variables, \(\partial v/\partial n = 0\). If, moreover, the force F does not depend on the flow rate v, \(\partial F/\partial v = 0\), so that eq. (2) becomes

$$\frac{\partial f}{\partial t} + v \frac{\partial f}{\partial n} + F \frac{\partial f}{\partial v} = 0$$  \hspace{1cm} (3)

This is similar to the Liouville equation of classical mechanics, and has the familiar form of the Vlasov equation for collisionless plasmas [12].

For universal collaboration in which the time rate of fractional change in the velocity is directly proportional to the sum of the fractional change in the density of production units at the other locations in the chain, F can be written as (minus) a gradient of a potential \(\Phi\) that satisfies a Poisson equation

$$\frac{\partial^2 \Phi}{\partial n^2} = -\left[\frac{V_0^2}{N_0}\right] \int dv f_1(n,v,t)$$  \hspace{1cm} (4)

denotes the perturbation of the distribution function from its steady state value [10]. When \(\int dv f_1(n,v,t) = \delta(n-n_0)\), this gives the simple Green's function

$$G(n-n_0) = \left(\frac{V_0^2}{N_0}\right)\left[-U(n-n_0) + U(n_0 - n)\right]$$  \hspace{1cm} (5)

showing that excess inventory higher up the chain promotes decreased production rates, whereas excess inventory lower in the chain promotes increased production rates.

To describe the effect of nonuniversal collaboration, we replace eq. (5) by

$$\frac{\partial^2 \Phi}{\partial n^2} - k_i^2 \Phi = -\left(\frac{V_0^2}{N_0}\right) \int dv f_1(n,v,t)$$  \hspace{1cm} (6)

an equation resembling the simple Debye-Huckel potential equation of electrolyte theory. This has the Green’s function solution

$$G(k_i; n - n_0) = \left(\frac{V_0^2}{N_0}\right) e^{-k_i|n-n_0|}$$  \hspace{1cm} (7)

describing a situation where a production unit density perturbation at any point \(n_0\) in the chain promotes a fractional change in the production unit velocity at any other point \(n\) in the chain that decreases exponentially with the distance \(|n-n_0|\) the other point is from \(n_0\). The scale length of the drop-off in the effect is \(1/k_i\). Thus, by varying \(k_i\), we can see what the effect of IT exchange extent is on the production unit velocity.

The dispersion equation for a normal mode is obtained by assuming a disturbance in the distribution function of the form

$$f(n,v,t) = f_0(v) + f_1(v) e^{i\omega t - ik_n}$$  \hspace{1cm} (8)

Then eqs. (3) and (4) become to the lowest order in \(f_1(v)\)

$$i(\omega - kv)f_1 = -ik\Phi f_1$$  \hspace{1cm} (9)

$$\Phi_1 = \left[\frac{1}{k_i^2 + k_n^2}\right] \left[\frac{V_0^2}{N_0}\right] N_1$$  \hspace{1cm} (10)

with

$$N_1 = \int dv f_1(v)$$  \hspace{1cm} (11)

We get on integrating eq. (9) over v and inserting the result into eq. (10):

$$D(\omega,k) = 0$$  \hspace{1cm} (12)
where

\[ D(\omega, k) = 1 + \left[ \frac{k}{k^2 + k_f^2} \right] \frac{\Omega_0^2}{N_0} \int dv \left[ \frac{1}{\omega - kv} \right] \frac{\partial f_0}{\partial v} \]  

(13)

and where the integral over the singularity at \( \omega - kv = 0 \) gives (10)

\[ \int dv \frac{\partial f_0}{\partial v} \left[ \frac{1}{\omega - kv} \right] = \] \[ PP \int dv \frac{\partial f_0}{\partial v} \left[ \frac{1}{\omega - kv} \right] - i\pi \left( \frac{1}{k} \right) \frac{\partial f_0(\omega)}{\partial v} \]  

(14)

The dispersion relation \( D(\omega, k) = 0 \) gives the value of \( \omega \) for the normal mode of wave number \( k \). Equation (14) shows that the mode is either damped or growing, depending on the sign of \( \partial f_0(\omega/k)/\partial v \).

When an external “force” \( F_{ext} \exp(i\omega t - ikn) \) is applied to the chain in order to damp the normal mode inventory oscillation of the same form, then the total force consists of the sum of the external force plus the internal gradient force described above.

\[ F(n, t) = [F_{ext} + ik\Phi]e^{(i\omega t - ikn)} \]  

(15)

Insertion of this force into eq. (3), and repetition of the foregoing algebra gives directly

\[ N_1 = \left[ \frac{1}{D(\omega, k)} \right] F_{ext} \int dv \frac{\partial f_0}{\partial v} \left[ \frac{1}{\omega - kv} \right] \]  

(16)

This shows that the external force is most effective when \( D(\omega, k) = 0 \), i.e., when the frequency is chosen to be that of the normal mode that is the target of the damping effort.

In earlier work, a second order calculation in the perturbation amplitude shows that the time evolution of the zero order distribution function \( f_0 \) satisfies a diffusion-like equation [11]. This is the same type of behavior observed in the quasilinear description of plasmas [13]. For our current purposes, however, it is only necessary to observe from eq. (16) that an external force is most effective in damping oscillations when it contains frequencies equal to those of the natural normal modes of the system.

### 2.2 Normal mode results

In the foregoing, a dispersion relation has been derived for the inventory oscillation normal modes of a supply chain when the extent of collaboration is limited, i.e., when the effect of an inventory perturbation at one location in the chain on the flow rate of production units at another location, dies off exponentially with the distance apart of the two locations. The dispersion relation resulting from this exponential decrease is given by eq. (12). The main feature of the dispersion relation can be obtained by ignoring for the moment the small imaginary term introduced by the integration over the singularity, and writing the dispersion relation in terms of a dimensionless frequency \( \Omega \).

Accordingly, write

\[ \Omega_0 = \frac{1}{T} \]  

(17)

where \( T \) is the processing time of a unit at any company in the chain (assumed for simplicity to be the same for all companies in the chain). Then introduce the dimensionless frequency

\[ \Omega = \omega T \]  

(18)

(Note that \( k \) is already dimensionless since it is the Fourier transform variable for the dimensionless location number \( n \).)

On ignoring the small imaginary term in eq. (14), the dispersion relation gives two results for \( \Omega \)

\[ \Omega_+ = k + \left[ \frac{k^2}{k^2 + k_f^2} \right]^{1/2} \]  

(19)

\[ \Omega_- = k - \left[ \frac{k^2}{k^2 + k_f^2} \right]^{1/2} \]  

(20)

Note two extreme cases:

**Case 1.** \( k_i > k \)

\[ \Omega_+ \approx \Omega_- \approx k \]  

(21)

**Case 2.** \( k_i > k < 1 \)

\[ \Omega_+ \approx - \Omega_- \approx 1 \]  

(22)

Case 1 occurs when \( k_i \) is large, i.e., when the time rate of change of flow velocity at any location is only affected by inventory perturbations very close to that location. In that case, the frequency is approximately proportional to the wave number, i.e., the normal mode resembles a sound wave.

Case 2 occurs for relatively long wavelengths \( (k < 1) \) when the time rate of change of flow velocity at any location is affected by inventory perturbations even if they are very distant from that location. This is the case referred to in our earlier work as universal IT exchange. In that case, the oscillation frequencies are essentially independent of wave number. In that sense,
the normal mode resembles a plasma oscillation. Here the effective plasma frequency is simply the inverse of the processing time at any location. The frequency with the negative sign designation corresponds to a wave moving in the backwards direction.

To generalize the results, \( k \) can be assigned any arbitrary value. Figure 1 shows the dimensionless frequencies \( \Omega_+ \) and \( \Omega_- \) for \( k = 0.05, 0.17, \) and 0.5.

![Graph](image)

**Fig. 1.** Dimensionless frequencies \( \Omega_+ \) and \( \Omega_- \) vs. wave number \( k \) for \( k = 0.05, 0.17, \) and 0.5. These \( k \) correspond to collaboration between an average of 20, 6, and 2 companies, respectively. In both Figures 1(a) and 1(b), the curves closest to the horizontal axis are those for \( k = 0.5 \) (least number of companies for IT exchange), whereas those farthest from the horizontal axis are those for \( k = 0.05 \) (largest number of companies for IT exchange).

It is also of interest to display the dimensionless phase and group velocities of the normal modes. The dimensionless phase velocity is \( \frac{n}{k} \) and the dimensionless group velocity is \( \frac{dn}{dk} \).

The dimensionless phase velocity \( \frac{n}{k} \) is of interest in connection with calculating the small imaginary term in the dispersion relation, since eq. (12) shows that this term occurs when \( \frac{n}{k} = 1 \). This corresponds to the actual phase velocity \( \frac{n}{k} \) having the value \( V_0 = \frac{1}{T} \).

The dimensionless group velocity \( \frac{dn}{dk} \) is of interest because it gives the velocity at which a packet of waves with wave numbers centered about a particular \( k \) moves along the supply chain. The actual group velocity of the packet is

\[
\frac{d\omega}{dk} = V_0 \frac{dn}{dk}
\]

Figure 2 displays the dimensionless phase velocity \( \frac{n}{k} \) vs \( k \) for the same three \( k \) as used in Figure 1.

Figure 3 displays the dimensionless group velocity \( \frac{dn}{dk} \) vs \( k \) for the same three \( k \).
2 Normal mode implications

This section of the paper has generalized earlier results that showed that supply chain normal modes resembled sound waves when behavior was influenced only by nearest neighbors, and resembled plasma oscillations when collaboration was universal. This has been done by introducing an exponential Debye potential that allows collaboration to drop off exponentially with the distance between two companies in the chain length. This leads to a frequency dependence on wave number, the form of which depends on the exponential drop-off distance of the collaboration.

It is particularly interesting that no threshold value exists for the number of companies collaborating at which a sudden first order phase transition occurs in the behavior of the normal modes. It might have been expected that a phase transition occurs similar to the sudden change in water from its liquid state to its solid state (ice). Rather, the normal modes with wavelengths smaller than the number of collaborating companies simply behave like plasma oscillations, while the normal modes with wavelengths larger than the number of collaborating companies simply behave like sound waves.

It is also interesting that an individual company participates with other companies in forming a normal mode not by knowing the details of each of the other companies’ inventory fluctuations, but only through a potential function that depends on a “detail-hiding” integral over the inventory fluctuations of the other companies in a collaborative group.

Equation (16) shows that external interventions to damp inventory oscillations are most effective if a Fourier component of the intervention has the same frequency as the corresponding supply chain normal mode. Accordingly, the form of the frequency dependency on wave number given by the dispersion relation is very important for determining optimum intervention.

Figure 1 displays the normal mode dimensionless frequency as a function of wave number for three different exponential scale factors \( k_1 = 0.5, 0.17, 0.05 \); corresponding to collaboration between an average of 2, 6, and 20 companies, respectively. For the exponential drop-off model, there are two distinct normal mode dimensionless frequencies (\( \Omega_+ \) and \( \Omega_- \)) for each wave number \( k \).

Figure 1a for \( \Omega_+ \) shows that an interesting transformation in the dependency occurs when the wave number is of the order of the inverse of the
exponential drop off scale, i.e. when \( k = O(k_i) \). This is especially evident for small \( k_i \), where a prominent knee appears in the curve of frequency vs. \( k \). For \( k < k_i \), the frequency rises very rapidly with increasing \( k \). Then when \( k > k_i \), the frequency increases more gradually with \( k \), corresponding to a plasma oscillation-like mode in the frame of reference moving with the steady state production unit velocity.

Figure 1b for \( \Omega < 0 \) shows the behavior of the frequency for backwards traveling waves. For small \( k \), the magnitude of the negative frequency increases as \( k \) increases, whereas for larger \( k \), the magnitude decreases as \( k \) increases. The smaller \( k_i \) is, the smaller is the value of \( k \) at which the maximum magnitude of the negative frequency occurs.

Figure 2 shows the dependence of the dimensionless phase velocity as a function of \( k \). For small \( k \) and small \( k_i \) – i.e. for long wavelength disturbances with a large number of companies involved in collaboration, the magnitudes of the phase velocity can become very large.

Figure 3 shows the dependence of the dimensionless group velocity \( \frac{dn}{dk} \) on \( k \). For the \( \Omega^+ \) modes, the group velocity can be quite large for small \( k \) when \( k I \) is small. For the \( \Omega^- \) modes, the group velocity is negative for small \( k \), but becomes positive for larger \( k \). The magnitude of the negative group velocities for small \( k \) is larger for small \( k_i \). The transition between negative and positive group velocities for the \( \Omega \) modes occurs at smaller \( k \) the smaller \( k_i \) is.

To summarize Section 2:

1. Inventory disturbances with wavelengths larger than the extent of collaboration \( (k < k_i) \), behave like sound waves.

2. On the other hand, inventory disturbances with wavelengths shorter than the extent of collaboration \( (k > k_i) \), behave like plasma oscillations. They all tend to share a constant oscillation frequency equal to the inverse of the processing time (assumed in the model to be constant for all the companies in the chain).

3. At short wavelengths \( (\text{large wavenumbers } k) \), both the phase and group velocities are limited.

4. At long wavelengths \( (\text{small wavenumbers } k) \), both the phase velocities and group velocities can become very large when the number of companies collaborating is large.

5. For any degree of collaboration between companies, the purchasing decisions for any particular entity in the chain does not require that entity to be aware of the individual inventory fluctuations of the other entities. Rather, the purchasing decisions are simply determined by a potential function that is in turn derived from integrations over the perturbed inventories of the collaborating companies.

The first two observations point out an interesting feature of supply chains in which each company collaborates with a large number of companies: For these chains, inventory fluctuations tend to occur at a constant frequency, independent of the wavelengths (and spatial extents) of the fluctuations.

The first two observations also point out that no sudden first order phase transition like the conversion of liquid water to ice occurs at some threshold value of the number of collaborative companies. Rather, normal modes with wavelengths longer than the number of collaborative companies simply behave like sound waves, whereas normal modes with wavelengths shorter than the number of collaborative companies behave more like plasma oscillations.

The third observation is useful for understanding both how small wavelength (and therefore relatively localized inventory oscillations) propagate, and also how to dampen short wavelength inventory oscillations. The fact that the velocities are limited can be advantageous for management control.

The fourth observation underlines how rapidly uniformity in the behavior of the companies in a chain is established when a large number of companies collaborate.

All of these observations indicate that the form of the normal modes for collaboration extending over several companies is advantageous for controlling unwanted inventory oscillations.

The fifth observation underlines the fact that a company does not need to directly know proprietary information about another company’s inventory in order to collaborate effectively in a group.

Although the emphasis thus far has been on inventory fluctuations and their damping, the normal mode approach is useful for a wider class of problems. For example, suppose an arbitrary time-dependent customer demand is imposed on the company at the end of the chain, and that company has a just-in-time inventory objective. These conditions can be considered as boundary conditions on the equations of Section 2.1. And the equations can be more easily solved by expressing the \( f(n,v,t) \) as a weighted sum over the normal modes, with the weighting function determined by the boundary conditions. The optimized time-dependent inventory of any entity in the chain can then be determined by an inverse Fourier transform over the normal modes.

3. Implementation of a collaborative manufacturing collective
The ingredients of a method for aiding companies to form an efficient collaborative manufacturing collective are contained in the analytic approach of Section 2 and in the LOGICS learning tool simulation game referenced in Section 1 [2, 3].

3.1 A common feature of normal mode-based analysis and LOGICS

Section 2 has shown that companies in a supply chain can collaborate effectively with each other to optimize operational strategies and reduce wasteful inventory fluctuations without requiring each company to exchange proprietary information directly with each of the other companies in the collaborative group. Each company needs only to determine its operational strategies from a potential function that depends on a detail-blurring integration over the inventory details of the other companies.

This was also the case for the learning object game immersed in complex systems (LOGICS). As currently constructed, the live participant plays the role of the retail purchasing agent at the end of a short supply chain. The other agents in the chain are autonomous and their decisions are based on algorithms derived from the Sterman beer game [1].

The player’s purchasing responses to his inventory fluctuations are based on any combination of three basic strategies: (1) he can follow his instincts; (2) he can invest in local IT to increase local rationality; and (3) he can invest in global IT that shares information universally in order to increase group rationality. In the third option, the player never knows the details of the purchasing decisions of the autonomous agents. The player can however follow their own intuition or follow the purchasing instructions provided to them by an optimized computer simulation of the Sterman algorithm, which itself takes into account the state of the chain. In the game, the rationality that is introduced is based on Sterman’s empirically determined Monte Carlo simulation. A cost is associated with each IT investment, as well as with bad purchasing decisions that lead to wasteful inventory fluctuations.

The three strategies were combined to create five participatory agent-based modeling and simulation (PABMS) designs. The game’s results to date have shown that the third strategy (global IT) generally give the lowest overall costs to the system. Performance feedback to the player was the only gaming technique used to test player performance across the five designs. Figure 4 is a box plot that shows the overall system costs across the five LOGICS designs.

Figure 4. Total System Costs by LOGICS Design number.

Design1 consisted of intuition-based ordering decisions by the player. The total system cost distribution was similar to that discussed in Sterman’s seminal “Beer Game” paper. Observations indicate that players of Design2 (repetition and coaching) performed better than players of Design1 (repetition only). Players of Design3 (PC ordering option added to Design1) appeared to have performed worse than players of Design1 and Design2. The range of the total system inventory cost distribution for Design3 increased over that of earlier designs. Players of Design4 (High Performance Computing ordering and hint added to Design3) appeared to perform better than players of the previous three designs. Total system cost range for Design4 was much smaller than Design3 and total system costs were reduced. Players of Design5 (per order feedback information added to Design4) appeared to have outperformed players of all other designs. Design5 total system costs were restricted across a lower range of scores and the values within that distribution represented lower total system inventory costs than all previous designs.

Especially interesting in the LOGICS experiments conducted to date is the observation that even though feedback in real-time was provided to the players that demonstrated the superiority of surrendering purchasing decisions to the empirically determined Sterman optimum purchasing strategy, many participants chose repeatedly to follow their own instincts. When this happened, it inevitably led to less than optimum performance.

Nevertheless, after several feedback demonstrations, the best players did surrender a majority of their purchasing decisions to the suggestions provided by the optimized Sterman simulation with consequent superior performance results. The key to superior performance was IT-enabled access to the algorithm and the willingness to trust the algorithm.

It is worth reemphasizing that in the third (global IT) option, the player never knows the details of the
purchasing decisions of the autonomous agents. He simply follows the purchasing instructions provided to him by the computer-determined Sterman algorithm which takes into account the state of the chain.

This is similar to the situation in Section 2 where the performance of each individual entity in the supply chain does not require that the entity have knowledge of the inventories of each of the other entities, but only of a potential function that is derived by a detail-smearing integration over the other inventories.

Both in the normal mode-based analysis of Section 2 and in LOGICS, collaboration was achieved without individual companies having to directly share sensitive information with each other.

3.2 Application to more complex systems

Finally, it is important to note that the analytic approach and the feedback learning effectiveness of the LOGICS learning tool are by no means limited to improving the performance of linear supply chains. Rather, the approach is applicable to more complex adaptive cloud-controlled manufacturing networks in which efficiency is achieved by cloud-mediated feedback to individual companies. The result should be a collaborative manufacturing collective that is more focused on overall system performance rather than reacting more or less randomly and wastefully. This more interactive “plasma” of coordinated entities generates actions that are closely tied to a desired optimal system level of output performance.

The main element of the proposed method for achieving an efficient collaborative production collective is the agreement of individual companies to base operational decisions on a system-wide (collaborative) algorithm rather than on intuitive locally-based decisions. This algorithm can be based on empirically determined optimal purchasing practices (as in the case of the Sterman algorithm in LOGICS), or preferably on a normal mode-based analysis of the system. Typically a sophisticated service provider would place an optimized normal mode simulation on the cloud. This would allow firms easy and cost-effective access to real-time system level rationality designed to minimize production waste. The service provider would use inputs from the individual companies as training data, to systematically improve production system performance. This allows collaborative firms to cooperate without having to share proprietary information directly with other companies.

4. References


