FROM BOTTLENECK IDENTIFICATION TO ENERGY DENSITY: INTEGRATING SEQUENCING INTELLIGENCE WITH THE THEORY OF CONSTRAINTS

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Abstract: In the contemporary era of smart manufacturing, modular software, and low-code automation, it has become much cheaper to make operational changes. But as technical capabilities become more accessible, a new risk appears: the busyness paradox. This happens when organizations take on too many improvement projects at once, using up resources without actually increasing their overall capacity. To address this performance-action misalignment, this paper introduces the strategic paradigm of sequencing intelligence—defined as the capacity to diagnostically analyze an operational system, identify the nodes holding the highest potential energy density, and prioritize executing those specific elements first—and integrates it with Eliyahu Goldratt's Theory of Constraints. This study proposes a scientific conceptual framework that redefines how organizational resources are allocated under a high level of uncertainty to systematically bridge the gap between the strategic prioritization process and operational execution to focus resources on the most important things. Using a multi-methodological approach that integrates Throughput Accounting principles with Markovian decision-making controls, we mathematically model the dynamics of Capacity-Constrained Resources. A detailed analysis of how organizations use energy, along with a two-dimensional Markov labor-switching model, shows that when teams try to optimize their own areas without coordination, it often looks good but actually causes major misalignment. This misalignment wastes important resources and working capital and does not improve overall results. This framework puts potential energy density ahead of pure execution speed, creating a clear, step-by-step approach to help organizations allocate resources more effectively. We find that the integration of Lean value-stream diagnostics with TOC thinking processes prevents organizational heat generation and stabilizes process variability prior to capital commitments. Therefore, we conclude that operations managers must adopt an "assay mindset"—prioritizing deep systemic diagnostics over raw execution speed—to successfully transition toward self-funding, phased overhauls. We outline how firms can establish self-funding, phased transformation pathways where each operational milestone directly capitalizes subsequent technical integrations. Ultimately, we suggest that future research should test potential energy density metrics in a range of high-variety manufacturing and engineer-to-order settings. This study provides a comprehensive foundation for operations managers seeking to manage the complexity of smart transitions while at the same time maximizing systemic cash-flow generation.
Keywords: theory of constraints, sequencing intelligence, operations management, process improvement

1. INTRODUCTION

In the past, operations management (OM) in large part was focused on technical skills and speed. Companies with the right technical resources to quickly develop software, automate machines, or adjust supply chains often stayed ahead of their competitors. However, today in the modern digital era, the cost of technical execution has collapsed to near zero. Automation tools are now widely available, modular low-code platforms are more common, and generative AI agents are being used more often. Together, these changes have turned execution from something rare and protected into a widely available service. When nearly any process, workflow, or system can be changed overnight, the main challenge is no longer how to get things done, but what to do first. Deciding the best order for process changes has become the most valuable skill in fast-moving operations.

Making technical tasks easier for everyone, while it seems helpful, causes a serious problem in factories and offices called the busyness paradox. Since changing processes now costs almost nothing, operations managers try to improve, automate, or digitize everything all at once. Departments often start separate projects in the name of continuous improvement. They focus on their own metrics, create automated scripts for smaller tasks, and roll out complicated digital transformation plans. The systemic result is a massive burn of organizational energy—manifested as cognitive load, operational friction, process disruption, and excessive coordination meetings—with little to no kinetic output in overall throughput. Running a manufacturing system or administrative workflow at full local capacity without coordinating specific constraints just wears out the organization's parts faster.

This study addresses the busyness paradox by introducing sequencing intelligence and combining it with Eliyahu Goldratt's well-known Theory of Constraints (TOC) (Goldratt & Cox, 1984, 1990). Sequencing intelligence means being able to study an operational system, find the nodes with the highest potential energy density, and focus on making changes at those points first. TOC explains how bottlenecks work and shows that improving a non-bottleneck does not increase the system's overall output. Sequencing intelligence builds on this by adding a dynamic approach that looks at physical energy and phased execution through the staircase strategy. It helps find the best way to implement changes by comparing the energy used for a process change with the results it produces. So, we must replace the traditional emphasis on execution velocity with a focus on potential energy density, establishing a theoretical-conceptual modeling framework that supports strategic sequencing in operations.

This study connects sequencing intelligence with TOC to address an important gap in current operations strategy research. Traditional methods like Lean and Six Sigma usually aim to eliminate waste throughout all processes (Nave, 2002; Pacheco et al., 2019). However, without constraint prioritization, these programs often fail to yield significant economic benefits, as confirmed by empirical studies on process-action misalignment (Inman et al., 2009). By integrating the "assay mindset"—the discipline of deep systemic diagnosis and deliberate non-action before execution with Throughput Accounting (Corbett, 1999; Gupta & Boyd, 2008), we demonstrate how a firm can identify "uranium" opportunities (high energy density constraints) versus "coal" opportunities (low energy density local optimizations). This approach creates a single operations theory that helps managers use a self-funding staircase strategy. With each step, cash flow and stability improve, making it possible to pay for the next technical upgrade.

To better understand this integration, it helps to compare Goldratt's "throughput world" with the traditional "cost world" approach that is common in standard management practice (Goldratt, 1990; Corbett, 1999). In the cost world, companies mainly try to boost profits by cutting costs. Since each department's expenses are shown on its balance sheet, managers try to make every asset, department, and worker as efficient as possible. They assume that improving each part will improve the whole organization (Gupta & Boyd, 2008). However, this approach does not work in systems where parts depend on each other because it overlooks the system's main constraint (Goldratt, 1990). In the throughput approach, system throughput is limited only by the bottleneck. This means that spending capital, time, or effort on improving anything other than the bottleneck does not boost total sales. Instead, it just increases inventory and operating costs (Corbett, 1999; Inman et al., 2009). With this key TOC idea as our starting point, we will break down the logic of sequencing intelligence in the next sections.

Furthermore, uncoordinated activity in non-bottleneck processes directly triggers what we term "the illusion of productivity." In legacy manufacturing settings, supervisors are rewarded for keeping their machines running and their workers busy at all times, regardless of whether there is actual market demand for the output (Goldratt & Cox, 1984). This behavior results in the rapid accumulation of raw material and work-in-process (WIP) inventories sitting in front of non-constraints. Today, this problem shows up in office workflows. Employees run automated scripts, hold frequent alignment meetings, and use generative tools to write endless reports. All of this creates a pile of digital data that no one can really use. This overactivity gives a false impression that the whole organization is making progress. In such a way, it is hiding the fact that the system's actual output is still limited. To solve this mismatch, we need a clear, structured change in how operations are managed, moving the focus from how fast tasks are done to how energy is used around the system's limits.

2. MATERIALS AND METHODS

This study uses a theoretical-conceptual modeling approach to mathematically formalize and systematically combine the main ideas of sequencing intelligence with the TOC. Instead of using retrospective bibliometric data-counting or descriptive keyword-collection procedures, which often overlook deeper meaning or clear guidelines (Luiz et al., 2025; Pacheco et al., 2019), we establish our methods on well-known existing operational systems theories. The methodological framework we are using here relies on three main pillars. First, Throughput Accounting (TA) that serves as the performance measurement system (Corbett, 1999; Inman et al., 2009). Second, we introduce the Potential Energy Density index, which is used as the strategic prioritization metric. Third, a threshold-based Markovian switching model represents how resources are allocated when capacity is limited (Aryanezhad & Komijan, 2010).

The first pillar, TA, gives the basic economic indicators that help connect shop floor decisions to the overall goals of the organization, avoiding the problems found in traditional cost accounting (Corbett, 1999; Gupta & Boyd, 2008). We define Throughput (T) as the rate at which the system makes money through sales, and we express it mathematically as:

$$T = S - TVC$$

where S represents sales revenue and TVC represents truly variable costs, which in a pure throughput-world perspective are restricted solely to raw materials, direct shipping, and sales commissions (Corbett, 1999; Hilmola & Gupta, 2015). Under this accounting logic, operating expenses (OE) include all other fixed costs—such as direct labor, administrative overhead, and depreciation—while inventory (I) captures all capital locked up in assets, equipment, and raw materials (Corbett, 1999). Operating decisions must be evaluated by their cumulative effect on increasing T, reducing I, or decreasing OE, with priority given strictly to throughput generation (Gupta & Boyd, 2008).

The second pillar is the potential energy density index. In physics, energy density is the amount of energy stored in a system or space per unit volume. For operational systems, we define Potential Energy Density (η_{pe}) as the ratio of the increase in systemic throughput (ΔT) to the total organizational energy input (ΔE_{org}) needed to make a process change. This input includes capital, time, and disruption.

$$\eta_{pe} = \frac{\Delta T}{\Delta E_{org}}$$

To create a complete operational metric, the denominator ΔE_{org} is broken down as a weighted sum of three different types of organizational friction: physical process disruption (ξ), cognitive and coordination complexity (ε), and direct capital expenditure (C):

$$\Delta E_{org} = w_1 \xi + w_2 \varepsilon + w_3 C$$

where w_1, w_2, and w_3 are measured weights related to the firm's specific situation. If w_1 is high, the system has serious physical setup or layout problems; if $w_2$is high, meetings, training, and management distractions take up most of the implementation time; and if $w_3$is high, money limits how much capital can be used. In high-performance automated environments, w_3 stays low since automation is inexpensive. However, w_2 becomes very high because the main problems are cognitive overload and misalignment between processes and actions. When η_{pe} is at its highest, process changes focus on a key systemic constraint, which leads to big increases in throughput with little resistance from the organization (like uranium). When η_{pe} is low, changes focus on areas that are not bottlenecks, using a lot of energy but making no real impact on the system (like coal).

The third pillar models the dynamic resource switching required to protect and elevate the system constraint. Following the threshold-based methods of Aryanezhad and Komijan (2010), we model a shop floor consisting of Capacity-Constrained Resources (CCRs) and Non-Constraints (NCs). Because of stochastic demand fluctuations and setup times, we define two control thresholds: an upper threshold (U) and a lower threshold (L) based on the ratio of buffer queue length (j) to active constraint manpower (i) (Aryanezhad & Komijan, 2010). We define the upper threshold switching indicator $B_{i,j}$, which determines when NC workers must be reallocated to the constraint queue, written as:

$$B_{i,j} = 1 \ if \ \frac{j}{i} \geq U; \ 0 \ otherwise$$

On the other hand, we define the lower threshold switching indicator $A_{i,j}$. This indicator shows when workers can safely go back to their usual NC stations because the constraint buffer has been used up enough:

$$A_{i,j} = 1 \ if \ \frac{j}{i} \leq L; \ 0 \ otherwise$$

One important factor in sequencing intelligence is the disruption that happens when a worker changes roles. When a worker moves from an NC station to a CCR, it takes some time, called reorientation time (θ), during which the worker is not productive. If the parts arrive at a rate of λ, we can model the effective NC manpower, $w_{nc}(t)$, using the transition state indicator *ξ(t)*. This indicator is 1 when the worker is reorienting and 0 at other times:

$$w_{nc}(t) = w_{nc} - \xi(t)\, \theta\, \lambda$$

Here, w_{nc} stands for the nominal average number of NC workers. When we solve the steady-state probability equations, we find the total output rate of the Capacity-Constrained Resource (CCR) using the transition state probabilities $\pi_{i,j}$, as shown below:

$$Output = \sum C_{i,j} \pi_{i,j}$$

where $C_{i,j} = \min(\mathrm{i}, \mathrm{j})$ shows the active processing capacity in state (i, j). If η_{pe} is at its highest, $w_{nc}(t)$ and $w_{ccr}(t)$ stay balanced over time, and simply the system reaches its best steady output while avoiding the local optimization loops that cause the busyness paradox (Aryanezhad & Komijan, 2010).

Bringing together these three mathematical pillars creates a strong conceptual model. To understand how the model behaves as a whole, we look at its dynamics under random processing and demand conditions. By comparing a system that uses sequencing intelligence (maximizing η_{pe}) with one that relies on local utilization metrics (the cost-world or builder approach), we can use math to find the exact conditions that lead to the busyness paradox.

This theoretical approach offers a solid mathematical way to study how stable worker reallocations are when random disruptions occur. In typical job shop scheduling, workers often switch tasks without a set plan, which causes a lot of transition noise and makes both constraint and non-constraint processes less stable. By setting clear upper and lower control limits, we show there is an ideal "strategic zone" where moving workers to the constraint brings more benefits than the loss in transition capacity (θ) (Aryanezhad & Komijan, 2010).

3. RESULTS

The theoretical and conceptual modeling followed by mathematical analysis provide important insights into how to prioritize process improvements. The results are shown below, organized into three main themes: the diagnostic alignment of Lean-TOC frameworks (the assay mindset), the order of capital use in self-funding paths (the staircase strategy), and the overall productivity problem caused by uncoordinated technology use.

First, our conceptual modeling of the pre-implementation phase shows that using Lean's Value Stream Mapping (VSM) together with TOC's Thinking Processes (TP) creates a strong diagnostic tool, similar to the academic idea of the assay mindset (Librelato et al., 2014; Moyo & Emuze, 2023). While traditional Lean applications jump directly into physical waste-reduction actions (the builder archetype), they often result in localized optimizations that fail to shift the overall system throughput. The current reality tree (CRT) is a tool that helps map out cause-and-effect relationships and reveals hidden policy constraints before any changes are made (Kim et al., 2008). By analyzing process flows conceptually, we find that the "assay mindset" prevents the waste of organizational energy by restricting Kaizen events strictly to those nodes carrying high potential energy density (η_{pe}). This is in strong agreement with previous qualitative assessments in the service and healthcare sectors, where identifying systemic constraints was proven to be the sole prerequisite for sustainable process improvement (Datt et al., 2024).

Second, the mathematical analysis of the potential energy density index validates the importance of the staircase strategy for capital sequencing. Traditional operations strategy often advocates "big-bang" technological rollouts (such as massive Enterprise Resource Planning or robotic automated lines) that require massive upfront capital expenditure (C) and trigger severe process disruption (ξ), resulting in a major drain on organizational resources. In our potential energy density framework, these interventions have very low η_{pe} scores. This is simply because the denominator increases because of costly capital expenditures (C), while the numerator does not change until the system will be fully integrated and operational to bring gains that will increase systematic throughput. A staircase strategy means focusing on simple, low-cost but effective process improvements (Goldratt, 2009; Telles et al., 2026). These steps can have a big impact, especially by increasing the numerator of the Potential Energy Density equation. Early changes like these help stabilize the shop floor, reduce cycle times, and quickly increase cash flow.

Third, our analysis looks at the Solow productivity paradox in relation to Industry 4.0 and affordable digital tools. When we view uncoordinated technological change as growth in different digital capabilities, the firms often fall into a systemic "efficiency trap" (Song et al., 2026). When digital tools are cheap, departments can build, optimize, and deploy ten wrong processes in a week, rapidly accelerating the production of non-critical tasks. Song et al. (2026) empirically demonstrated that unaligned digital transformation efforts in many different directions decrease total factor productivity by creating an efficiency trap that is characterized by high local activity but at the same time stagnant systemic output. This is the busyness paradox. When focus only on working faster, like a builder, but ignore the need to plan and prioritize, like an assayer, you end up using all your resources without making real progress.

Finally, when analyzing supply networks between organizations that face uncertain demand forecasts, it is important to consider how specific capacity alignment will impact outcomes. In systems with multiple suppliers, buyers often inflate their forecast reports to secure enough supply, which can cause serious capacity misalignment (Li et al., 2023). Li et al. (2023) found that when there are more component suppliers, coordination failures become much worse. Because suppliers expect buyers to overdraw forecasts, they ignore these reports and instead base their capacity decisions on previous demand information they have. This specific behavioral mismatch creates a permanent supply chain bottleneck in which capacity is simply misaligned. So, as information dissemination or execution speed increases, we cannot resolve such bottlenecks without explicit capacity synchronization and sequencing intelligence.

To put these findings into perspective, we can look at how managers have typically handled schedule disruptions in real workplaces. In traditional systems, when a schedule falls behind, managers often react by bringing in extra workers, starting several urgent tasks, and requiring overtime at every station. Under our mathematical switching model explained above, this uncoordinated reaction simply increases the transition frequency and the reorientation time loss (θ), degrading the total system output rate. Conversely, when sequencing intelligence is applied, managers understand that only the active constraint buffer matters. They use capacity in non-constraint resources to keep the system stable. This lets the NC stations handle changes and only help the CCR when the upper limit (U) is reached.

4. DISCUSSIONS

The findings of this study suggest a fundamental paradigm shift in the strategic focus of operations management. In the legacy world, execution was slow, expensive, and difficult, which naturally acted as a protective buffer, preventing managers from making too many mistakes too quickly. Under the new paradigm of cheap and democratized technical execution, this protective buffer is eliminated. If an operations team can build anything overnight, the strategic premium shifts entirely to cognitive, diagnostic, and sequencing capabilities. This shift is conceptualized as the transition from the legacy 'builder' archetype to the modern 'assayer' archetype.

The Builder vs. Assayer Archetype comparison simply summarizes these differences across five distinct dimensions. In terms of **core premise**, the Builder believes that being able to execute is the primary differentiator, whereas the Assayer recognizes that execution is a commodity and picking the correct sequence is the only differentiator. When it comes to **metrics**, the Builder mainly cares about how quickly things get done and how well resources are used in specific areas. This focus often leads to what is called the busyness paradox. In contrast, the Assayer looks at potential energy density (η_{pe}) and overall system throughput (T). When it comes to **strategy**, the Builder usually tries to optimize and improve in many directions at once, while the Assayer prefers a step-by-step approach that funds itself along the way. In terms of **mindset**, the Builder defaults to immediate action and constant change, whereas the Assayer practices "deliberate non-action"—strategic pauses to study, diagnose, and map the underlying system before acting. Finally, when it comes to **failure modes**, the Builder often faces problems with organizational breakdowns and high resource use. The main risk for the Assayer is getting stuck in analysis paralysis if there are no clear limits on diagnostic pauses.

Looking at these archetypes helps explain why many digital transformation programs fail today. Organizations with a builder mindset often confuse being busy with making real progress. When they focus on improving efficiency in individual departments, they end up with lots of small improvements that do not address the main bottleneck (Goldratt, 2009). On the other hand, someone with an assayer mindset sees a "strategic pause" as a valuable way to diagnose problems, not as wasted time. Telles et al. (2026) found that even in ideal "greenfield" situations, new manufacturing systems do not start out lean. Instead, they become more efficient over time by moving through stages of design, buffer management, and adapting to constraints. This kind of progress only happens when organizations focus on learning and improving the whole system, not just working faster. Furthermore, our threshold-based Markovian switching model highlights the importance of systemic capacity buffers and protective capacity. In high-variety manufacturing and engineering-to-order (ETO) environments, setup times (θ) and process variability are extremely high (Telles et al., 2020). When NC resources are used at their highest local efficiency, there is no extra capacity left to help the CCR during unexpected demand spikes. As a result, lead times rise quickly and due-date performance drops (Goldratt, 2009; Hilmola & Gupta, 2015). In the sequencing intelligence framework, we see that focusing on NC efficiency is misleading. NC resources must maintain latent capacity (systemic slack) so they can dynamically switch to assist the constraint based on the upper threshold (U) and lower threshold (L) status (Aryanezhad & Komijan, 2010). Thus, sequencing intelligence provides the mathematical logic to balance the tension between execution velocity and systemic protective capacity.

This way of breaking down the theory has a big impact on how we think about organizational change. Traditional improvement models see change as a steady, ongoing process where more change is always seen as positive. On the other hand, the sequencing intelligence approach views organizational change as something that happens in unpredictable, uneven steps. Every change adds coordination challenges and mental effort, so there is a clear limit to how much change an organization can handle at once. If this limit is passed, the organization can become chaotic. When managers use the potential energy density metric, they can help protect their organization's ability to handle change. This approach makes sure that changes happen at a pace and order the organization can manage.

5. CONCLUSIONS

This study combines the strategic framework of sequencing intelligence with the TOC to build a clear, math-based approach for operations management. Rather than focusing on how fast tasks are done, we look at potential energy density to solve the busyness paradox in fast, automated settings. Our models show that making uncoordinated changes in non-bottleneck areas leads to significant waste. In contrast, focusing efforts on CCR increases throughput and creates self-funding liquidity through a staircase strategy. Also, it is a practical guideline for operations managers working through digital transformation and AI adoption. First, managers should avoid rushing into action and instead take time to map out systems thoroughly before starting automation. Second, change programs should follow a staircase approach, using self-funding and phased milestones. Third, instead of using local departmental efficiency metrics, managers should switch to Throughput Accounting metrics to avoid the local optimization loops that lead to the busyness paradox.

This research has some limitations, which open up new directions for future studies. Our conceptual model is exploratory and relies mainly on qualitative evidence. Although the mathematical ideas behind potential energy density and Markovian threshold switching are strong in theory, they still need to be tested with data from more industries. Future studies should create survey tools and use structural equation modeling to check how sequencing intelligence affects a firm's productivity and financial results.

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