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The implementation of 5S lean tool using system dynamics approach

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Abstract

The 5S (sort, set, shine, standardize and sustain) lean tool has been known to improve system performance. In the current study, the short run dynamic implications of the sorting aspect of 5S is investigated using system dynamics. A system dynamics model is developed for a manufacturing case study and simulated to establish the effect of sorting activity on manufacturing throughput. The purpose was to assess, in advance, the system performance outcomes when 5S practices are improved. The simulation results were the stimulus for real life improvements in the system because the simulation results were able to mimic the real-life outcomes. While the simulation results encourage further improvements to be implemented, the model developed in the current paper is replicable in other instances as the variables used in the model are generic and common to most types of manufacturing systems, particularly those new to lean practices. The dynamic analyses of 5S lean practices is not common. The study also reveals some interesting relationships between 5S and other lean practices and between 5S and system performance.

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Keywords:

1. Introduction

Lean manufacturing (LM) comprises a set of tools and practices, which when implemented properly and fully, help to improve system performance. The 5S lean tool is one of such. It is an acronym for sort, set in order, shine, standardize and sustain. They are sometimes given different names than those listed here, but they mean the same thing.

5S helps to reduce non-value adding time, increase productivity and improve quality [1]. It has been used in the design of efficient facilities [2]. 5S techniques have been integrated with other lean tools to reduce changeover time [3].

The 5S lean technique can be summarized as follows [4,5]:

1. Sort- To organize things in order, for ease of storing and retrieval.
2. Set- To designate and clearly label where everything should be stored. Everything should be kept in its rightful place to eliminate the need for searching.
3. Shine- To keep everything clean and neat.
4. Standardize- To document the work methods and make the 5s part of the culture of the organization.
5. Sustain- To form a habit of continuous improvement procedures.

If lean has not been firmly established in an organization, there is the tendency to go back to old ways of doing things. Lean practices that are meant to improve the system may be relegated in favor of ensuring more goods are processed. In the current article, we describe a simulation-based methodology that enables the systematic implementation, improvement and sustaining of 5S practices, while also improving throughput for a manufacturing system

2. Literature review

2.1. 5S lean tool

Kobayashi et al. [6], through an exploratory study of companies in different geographical regions, found that 5S was viewed differently. They established that Japanese companies emphasize 5S as a strategy for organizational excellence; something that is imbibed in workers in their

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private and work life. Meanwhile, UK- and US-based companies viewed it as a tool for the workplace organization only. They suggest that these views define the approach and eventual benefits of 5S.

The factors in an organization that enable 5S have been empirically investigated [1]. Factors such as firm size, product type, employee training and organizational attitude towards quality and continuous improvement affect the implementation of 5S and the system's performance after implementing it [1]. As it relates to product type, if a plant's customers are other manufacturers, the relationship is more likely to be dictated by quality and time, making it an incentive to implement 5S techniques in the supplier plant.

Bevilacqua et al. [3] integrated 5S strategies in a pharmaceutical plant. They implemented various 5S techniques that led to dramatic improvements in changeover time with less variability. For example, dedicated transport carts were designed to guarantee fewer mistakes when picking up items for reuse. Pictures of the parts and where they should be stored were clearly posted. They standardized procedures for accurate forecasting of time required to sort and find items, thereby reducing variability in the changeover time and process.

Gupta and Jain [7] described how to identify teams that would implement the 5S pracitces, generate a cause-and-effect document to be used for analysis and develop a data collection method, to ensure the right implementation of 5S. They also proposed the use of a 5S audit tool to ensure the regular application of 5S procedures.

5S has been demonstrated to be a simple and non-costly way to achieve tangible benefits of LM. Much effort has been dedicated towards listing ways of how to implement it, even to the extent of detailing the shopfloor day-to-day activities. Such information gleaned from the literature is often useful when identifying possible ways of improvement. What has not yet been demonstrated in the literature is the dynamic effect of a non, partial or full implementation of 5S on the performance of a system.

2.2. System dynamics modelling

System dynamics (SD) is a methodology used for understanding the cause and effect relationships that exist in a system, such as a manufacturing system. The simulation modeling aspect is intended to mimic a real-life situation, such that experiments undertaken in the model can give an idea about how the system will behave in reality and evolve over time, when the experiments are actually implemented. Sterman [8] as well as many others [9-15] have documented the step-by-step methodology of designing and using a SD modeling approach for decision making.

SD has been in existence since the late 50s: it is not a new problem-solving and decision-making approach. In other words, much has been researched in its use. We attempt to present only a few of the studies here, focusing on those that have been applied within a manufacturing system setting.

SD has been used: to investigate and improve productivity for a print shop [9]; to forecast the performance of a home appliances manufacturer, based on operational and financial measures [10]; to investigate the dynamic performance of a manufacturing cell under demand variability [11]; to analyze the cost performance dynamics of production levelling in a manufacturing cell [12]; to quantify the effect of lean-based improvement options on lead-time [13] and as a lean assessment tool [14].

From aforementioned, SD proves fruitful in addressing manufacturing related problems. In the current article, we use an SD approach to investigate how the sorting activity impacts manufacturing throughput in a case study of a manufacturing system. The SD model, though simulation experiments, would then be used to establish the magnitude of improvements in throughput as sorting time is decreased. The simulation results are intended to provide the motivation to implement, improve and sustain 5S practices in the system. Fig. 1 describes the methodological steps.

3. Description of the problem

A typical problem in many small and medium sized manufacturers is the variation in throughput due to a variety of reasons such as demand fluctuations and system inefficiencies for example, breakdowns and inaccurate schedules. In the current article, the case of a make-to-order print packaging manufacturing system is presented. The company experiences seasonal demand and there are seasons of high and low demand.

In low demand season, the system copes well and items are properly sorted and stored in their rightful places. The plant is generally neat and tidy. The reverse is the case in high demand periods: the plant managers are overwhelmed and more concerned with meeting customer delivery due dates than with maintaining a well-arranged plant. The situation is a "fire-fighting" approach to lean implementation until the high demand season ends. The situation is cyclical and has been going on since the plant introduced lean a few years ago. The company often loses customers during this period when they miss the delivery due dates. Although the company operates different delivery due dates because of different order sizes and different job order specifications, a single target manufacturing lead time has been assumed.

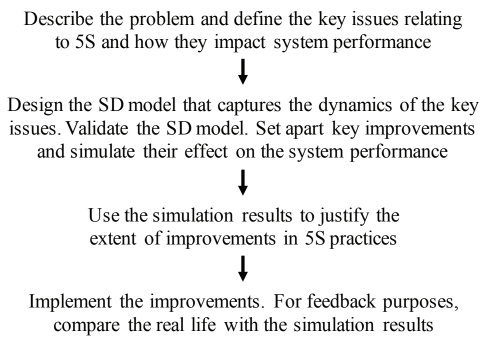

Figure 1. The methodology describing the use of SD to improve 5S implementation and

While this is necessary for building the SD model (as multiple targets may not be easily configured), the assumption is sufficient for the study purpose since the manufacturing lead times for all (or majority of) jobs will tend towards a mean. The objectives that were mapped out for this case are to:

- use the sorting situation to explain the throughput problem;
- use SD to communicate the dynamic implications of the sorting issue;
- use the SD model as a tool for the simultaneous improvement of 5S and manufacturing throughput.

4. Design and use of the system dynamics model

4.1. Design of the SD model

The SD model described in the current article has been designed using AnyLogic. The dynamics of a system are led by the variables that are represented as stock and flow variables of the SD model [8]. The SD model used in the current analysis is shown in Fig. 2.

The dynamics behind the model is straightforward. Manufacturing lead time is measured against a target level. The higher the gap, the more the pressure to attempt to reduce the gap. The higher the pressure to reduce the manufacturing lead time gap, the more the managers and employees cut corners by spending less time doing things that they believe will not directly increase the throughput. There is less time assigned for sorting activities, which reduces the rate of sorting and increases the stock of un-sorted items (sorting backlog). Meanwhile when items are left unsorted, it creates chaos in finding items for re-use, and so time is spent looking for tools for setup and for machine repairs. The increased times taken to setup and repair machines increases the normal manufacturing cycle time which further reduces the throughput and lead time, thereby aggravating the initial problem.

The dynamics in the system are driven by the two reinforcing feedback loops (Finding Tools For Setup and Finding Tools For Repair) and one balancing feedback loop (Throughput Effort). The reinforcing loops aggravate the throughput situation while the balancing loop attempts to reverse the situation. The overpowering strength of one set of feedback loops above the other defines the mode or state of the system's behavior over time.

The variables used in the SD model are typical of most production settings, thereby ensuring that the SD model can be replicated in other non-MTO manufacturing system types.

4.2. The governing equations of the SD model

Governing equations are used to define the relationships between the cause and effect variables. The equations enable the SD model to be simulated. Table 1 lists the equations that were used for the SD model. The value for Normal Production Capacity is the same as Order Entry Rate. This leaves no availability in the system, making the situation critical. Some equations are based on law of factory physics for example Throughput and Lead Time (see Table 1).

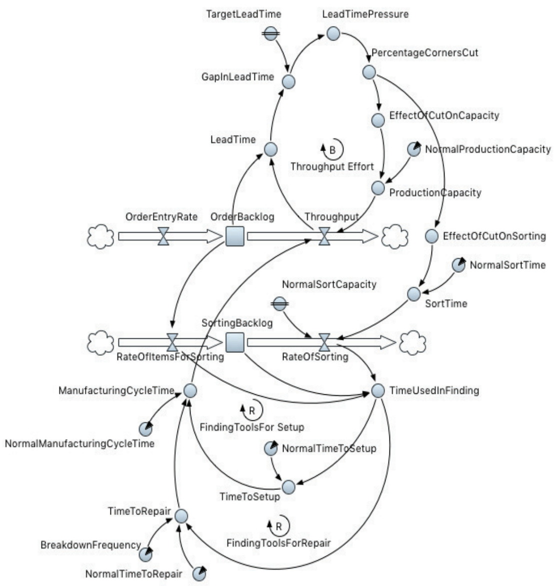

Figure 2. The SD model depicting the dynamic implications of sorting

Other equations are based on logic for example Setup time is increased when more time is used up in finding tools. Meanwhile, nonlinearity exists between other variables for example "*Gap In Lead Time*" and "*Lead Time Pressure"* (urgency to reduce the gap). This type of qualitative-based relationship can best be described using a Table Function of values that are gleaned from archival data combined with logically plausible assumptions [8].

Fig. 3 is the graph of the Table Function used in defining the relationship between "*Gap In Lead Time*" and "*Lead Time Pressure"* for the current case.

For the purpose of the current analysis, lead time pressure has been linked with additional workhours required to reduce lead time gap. With reference to Fig. 3. from previous experiences in the system, there is little or no pressure when the gap is below 2 days. When the gap increases to 6 days, the pressure is increased by about 20% i.e. workhours need to increase by approximately 20% to reduce the lead time gap to acceptable levels. When the gap exceeds 12 days, the pressure is increased by about 50% but maintains at this level. It is assumed that pressure does not exceed 50% as there is often a limit to which the system can stretch itself. This relationship is defined as a Table Function and labeled as "*Gap_Pressure"* in the SD model developed for the current case. The formula for deriving *LeadTimePressure* is then defined by Equation 1:

$$LeadTimePressure = Gap\_Pressure(GapInLeadTime) \quad (1)$$

Equation 1 implies that Lead Time Pressure is a function of Gap in Lead Time, and the relationship is summarized within a Table Function. Lead Time Pressure is called (looked) up from within the Table Function, for every Gap in Lead Time. Sterman [8] documents how Table Functions can be generated for situations where data is sparse.

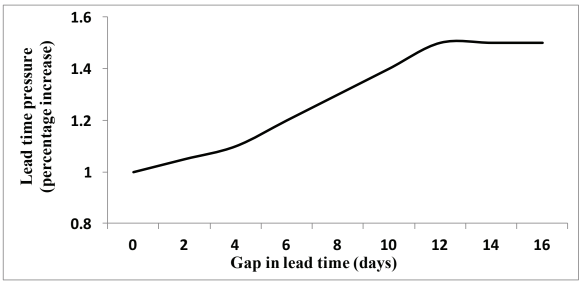

Figure 3. Graph describing the qualitative and non-linear relationship between gap in lead time and pressure to reduce the gap.

4.3. Validation of and experimentation with the SD model

The SD was simulated for a period of 30 days, the results of which are summarized in Fig. 4a. Three variables in the SD have been set apart for further analysis: *Throughput*; *TimeUsedInFinding* and *LeadTime* A 30-day simulation period was chosen because it gives sufficient time for the effects of changes to be evident. Whereas, it provides ample time to quickly validate the simulation results in the real system.

Table 1. List of equations used in the SD model

Variable in the SD model	Formula
OrderEntryRate	Value = 30 orders
OrderBacklog	d(OrderBacklog)/dt = OrderEntryRate - Throughput Initial value = 35 orders
Throughput	ProductionCapacity / ManufacturingCycleTime
LeadTime	OrderBacklog / Throughput
TargetLeadTime	Constant, Value = 4 days
GapInLeadTime	LeadTime - TargetLeadTime
LeadTimePressure	Gap_Pressure(GapInLeadTime)
PercentageCornersCut	LeadTimePressure
EffectOfCutOnCapacity	PercentageCornersCut
NormalProductionCapacity	Value = 30 orders
ProductionCapacity	EffectOfCutOnCapacity * NormalProductionCapacity
EffectOfCutOnSorting	PercentageCornersCut
NormalSortingCapacity	Value = 30 orders
NormalSortTime	Value = 1 day
SortTime	NormalSortTime * EffectOfCutOnSorting
RateOfItemsForSorting	OrderBacklog
SortingBacklog	d(SortingBacklog)/dt = ORateOfItemsForSorting - RateOfSorting Initial value = 35
RateOfSorting	SortingCapacity / NormalSortTime
TimeUsedInFinding	(SortingBacklog/RateOfSorting) / RateOfItemsForSorting
TimeToSetup	NormalTimeToSetup + TimeUsedInFinding
NormalTimeToSetup	Value = 0.05
TimeToRepair	(TimeUsedInFinding + NormalTimeToRepair) * BreakdownFrequency
NormalTimeToRepair	Value = 0.11
BreakdownFrequency	Value = 0.2
ManufacturingCycleTime	NormalManufacturingCycleTime + TimeToRepair + TimeToSetup

It can be seen from Fig. 4a that, over time, the system degenerates in terms of throughput (completed orders per workday) and time used in finding tools for setup and repair. Throughput for example drops steeply from 28 completed orders per day to 24 completed orders after 15 days and maintains at this level for the next 15days. A similar trend occurs in the actual system at the onset of a high demand season whereby throughput drops quickly but stabilizes at between 20-25 completed orders per day: the minimum threshold of the system.

The various times used in finding tools are summed up for the 8-hour work day. The simulation model indicates an increasing trend over the 30-day period from less than one-tenth of the workday to about 0.6 day (or 4.8 hours in total). This mimics the real trend as orders build up and items are misplaced on the shopfloor and on shelves. In the real system, a similar value was recorded on one particular workday. Each of the 50 shopfloor workers spent an average of 5 minutes looking for various items, the cumulative of which is about 250 minutes or 4.2 hours of the production workday.

Manufacturing lead time increases from 1 day to 15 days. This is often the trend when demand and workload increases. The company usually increases daily work hours in order to prevent manufacturing lead time from increasing continuously beyond 20 days.

Parameter variables in the SD model are not affected by other variables and are used to drive model behavior. Examples of parameter variables for the current SD model are N*ormalTimeTorepair*, *NormalProductionCapacity* and *NormalSortTime*. By altering the model values of these parameter variables, the SD model can be simulated to show how the system will respond when these variables are altered in reality. Although there are multiple parameter variables in the current SD model, the *NormalSortTime* variable is of interest in the present study. It has been taken as the key measure of 5S practices for the system. Had there been multiple parameters or measures of interest, a Design of Experiments methodology [15] or an Analytical Hierarchy Process [16] could be used to set apart the key improvements that should be advanced.

Normal sort time defines the cumulative time spent sorting items. In the current situation, a worker takes an average of ten minutes to sort (organize and store away) an item. There are typically about 50 different sorting requirements every day. On the whole, about 500 minutes (approximately 1 day of an 8-hour production shift) is spent sorting items every day. The time spent sorting one item may appear insignificant, but when accumulated over a production shift, it becomes meaningful. A decrease in normal sort time is desired and its effect on system performance is sought.

Based on the aforementioned, various values were inputted for *NormalSortTime* and the SD model was simulated for each alteration. Fig. 3b depicts how the system performances will likely change when normal sort time is reduced by 50%.

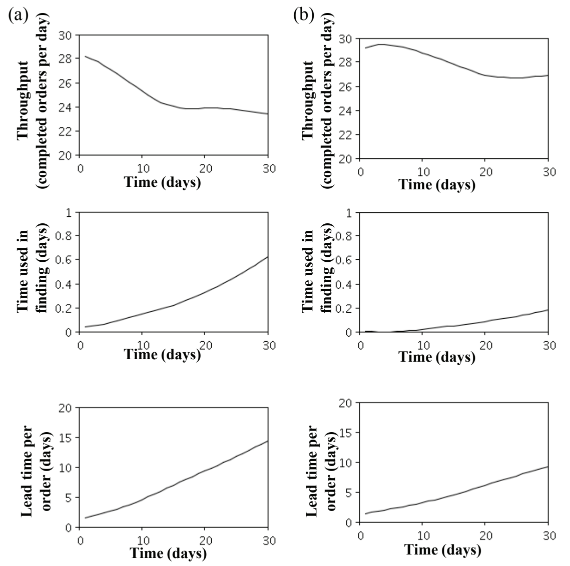

Figure 4. Evolution of the system over time: (a) current as-is; (b) with normal sort time reduced by 50%

The SD simulation results show that throughput increases slightly in the first few days, before dropping. The increase in throughput at inception is as a result of the improved efficiency level in sorting which provides a starting boost to the system before it is loaded with more job orders. The rate of drop in throughput is not as significant when compared to the current as-is. On the 30th day, the throughput is about 26.5 completed orders per day when compared to less than 24 completed orders for the current as-is. This is an improvement of 10% over the present situation.

The total time spent looking for items reduces from 0.6 to about 0.2 work hours per day. This is a 67% improvement in time spent looking for items. With this savings, workers can have more time doing more value-adding activities, while time spent in setup and repair activities decreases.

Manufacturing lead-time is affected by time-related losses along the various processes. With time saved in setup and repair, machine idle and stoppage time is reduced. Whereas, manufacturing lead time is reduced when throughput is increased. The improvements in throughput and time spent looking for items which have been achieved with the improvement in normal sort time have had a positive impact on manufacturing lead time which has improved by 33% at the end of the simulation run (See Fig. 4b).

5. Initiating an improved 5S strategy

Based on the improvements that could be attained as revealed with the simulation experiments, the authors conducted some work studies relating to how items are arranged for sorting and how they are retrieved for reuse. Currently, in the case study plant, there are dedicated cabinets and shelves for storing works-in-process, work item, tools and machine spare parts. Some job orders are delayed for various reasons and these form the works-in-process that needs to be stored on dedicated shelves. From the initial investigations, it was concluded that the “Sort” aspect was being adhered to. What was lacking in the system was 100% labeling of storage locations. It was noticed that workers found it easier (and were more motivated) to sort and find items in sections where there was full compliance of shelf labelling. The “Set” aspect was not fully adhered to. Items were not properly cleaned before storing and so when they are retrieved for reuse, they needed to be cleaned again, thereby adding to the time delay before they can be used. The “Shine” aspect was being partially implemented. There were no documented work methods and so there were variations in time taken to sort and find items. The “Standardized” procedures were lacking. Due to the partial- and non-compliance of the above aspects of 5S, the last aspect, “Sustain” could not yet be considered at the current situation. This is because the first four aspects needed to be fully implemented before the sustain aspect can be initiated.

Having identified the sorting issues that needed to be improved, the SD was used to establish the magnitude of improvement in throughput as normal sorting time is decreased step-wisely (see Fig. 5). This was needed to justify the extent to which the normal sorting time should be improved. This is because a considerable decrease in normal sorting time may not significantly improve throughput; whereas, decreasing the normal sorting time may require time, effort, training and some new shelves. From Fig. 5 it is obvious that throughput increases by approximately 40% when normal sort time is reduced by about 80%. This information acts as a justification to improve normal sorting time.

The graph of Fig. 5 also acts as a target check: it is expected that throughput will increase by 10% if the normal sort time is reduced by 50%. Based on the above analysis combined with opinions from managers in the plant who sought to reduce the normal sort time in small manageable decrements, the first strategy was to implement a 30% reduction and expect a 6% rise in throughput from 24.05 to 25.49 completed orders per day. The managers believed a 30% reduction was possible within a short period, and the results could be used to justify or disprove the need for further improvements. Fig. 6 is the picture of one of the shelves before and after sorting improvements were initiated. Sheets containing standardized times and activities relating to sorting were clearly pasted on each shelf. There was more lighting to quicken and improve search for items.

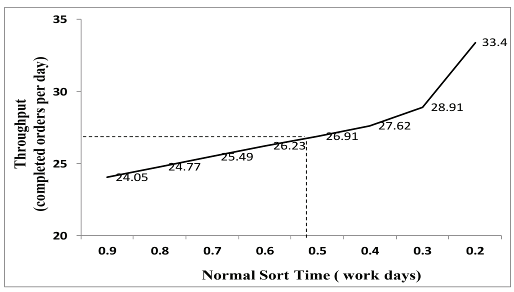

Figure 5. SD simulation results showing change in throughput for stepwise improvement in normal sort time

Workers were trained on the use the standardized time and standardized routine during each sorting activity. Some sorting and shining activities were carried out during changeover operations [3]. Some shelves compartments were clearly labelled with pictures of the part, tool or item. Maps were pasted at the entry to each storage section, indicating the general arrangement of items. All the improvements took approximately 2 weeks to implement. Since shelves were already in place, there were no major cost outlays. In order to attribute changes in throughput performance to changes in sorting behaviors, all other variables in the system were held constant as best as possible. After the two-week implementation, a study was conducted to establish the overall improvement in the average sort time and system throughput. The real-life results were compared to the simulation results, see Table 2. The time savings achieved by improving the sorting activity was used to reduce the additional man-hours that is often required when workload rises during the onset of the high-demand season.

Table 2. Simulation results compared to real life situation

Variable	Real life results	Simulation result	Variance between simulation and real life
Normal sort time (days)	0.76	0.76	0
Throughput (orders/day)	24.9	25.05	0.15

6. Study implications, conclusions and future outlook

The SD model was built and simulated to indicate how system throughput will improve as 5S practices are improved. The methodology advanced and used in the present study has shown the direct and unambiguous link between improvements in 5S and the impact on manufacturing system performance. It therefore supports the hypothesis often advanced in the literature, that lean practices improve manufacturing system performance.

While the methodology shows throughput improvements, it also shows improvements in other aspects of the system. For example, the impact of the sorting lean practice can be seen in other lean practices such as time used in setup and repair activities; two important aspects of Just in Time Management and Total Productive Maintenance. In other words, the effect of changes in one lean practice can be established on other lean aspects. With this kind of information, organizations have fore knowledge of the core aspects of lean they should be focusing on.

The methodology is able to assess, in advance, the outcomes of planned improvements in lean behavior. With the SD model being capable of replicating reality, the company was able to determine whether it should carry out improvements or not. The simulation encouraged the company's managers to adopt the methodology to improve other aspects of lean using an SD modelling technique.

(a)  (b) 

Figure 6. Shelf arrangement: a) before 5S improvement; b) after 5S improvement

The SD model developed in the current article is useable in other situations as the variables are generic, and are common to most types of manufacturing systems. It would be worth researching its application within plants of different manufacturing system types and in different levels of lean maturity. The methodology has initiated a case for investigating multiple aspects of lean simultaneously, as well as investigating their short term dynamic implications on the system. It would be worthwhile to investigate a wider range of lean practices as well as their long-term dynamic effects.

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