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# Decision Support Tool for Evaluating Push and Pull Strategies in the Flow Shop with a Bottleneck Resource

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**Abstract.** This paper gives an attempt to build a decision support tool linked with a simulation software called ARENA for evaluating and comparing the performance of the push and pull material driven strategies operating in the flow shop environment with a bottleneck resource as the shop's constraint. To be fair for such evaluation, the comparison must be made fairly under the optimal setting of both systems' operating parameters. In this study, an optimal-seeking heuristic algorithm, Genetic Algorithm (GA), is employed to suggest a systems' best design based on the economic consideration, which is the profit generated from the system. Results from the study have revealed interesting outcomes, letting us know the strength and weakness of the push and pull mechanisms as well as the effect of each operating parameter to the overall system's financial performance.

**Keywords:** Push and Pull Strategies, Genetic Algorithm, Simulation, Decision Support Tool, Bottleneck Resource.

## 1. INTRODUCTION

Decision support systems (DSS) are tools that an organization uses to support and enhance decision making activities. Their objective is to support a decision making process which is primarily a matter of reasoning (using the mental models of the system's designer) and analogizing (based on stories about similar events retained in mind). In this study, we intend to develop a decision support tool to assist in the design process of manufacturing systems. Manufacturing systems can be defined as tasks and processes appropriately indicating the three main functions of manufacturing systems including procurement, production, and distribution. In this study, we focus on the production system of flow shop, in which typical production systems operate by two types of production control mechanisms namely "push" and "pull" strategies.

In a push system, the production and movement of inventory items is determined by a preexisting schedule that authorizes a material issue of transfer, or the start of a production operation. Typically, the push system works well in environments where there is high customer demand and quick product turnaround times, in effect where there is a need to hold buffer stocks to cover customer demands, hence continuous production runs. Items

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are manufactured based on forecasted needs, following some types of production plan.

On the contrary, in a pull system, items are only produced when on demand for use or to replace those taken for use. In a material control context, this is the withdrawal of inventory as demanded by using operations. Material is not issued until a signal comes from the downstream stations or customers. Thus, a workstation pulls output from the preceding station as it is needed. Because the pull production process is designed to produce only what is deliverable, the business becomes leaner, as a result of not holding excessive stock levels of raw materials, work-in-process and finished goods. The pull system is also known as the kanban system as visual signals (kanbans) are used to let workstations know when parts need to be replaced.

## 2. LITERATURE REVIEW

Researches in production and manufacturing systems and the optimization techniques are vast. Here, we are going to introduce some of them to build the background knowledge. Many managers have recognized the importance of the capacity constrained resource (i.e. bottleneck) to the performance of their company. This critical resource determines the throughput rate of the system and therefore the ability to make money for the entire operation. In order to improve the throughput of the system, the throughput of the bottleneck has to be improved (Goldratt, 1992). The great majority of previous studies of production lines have assumed that real production lines are either perfectly balanced or nearly so (Powell, 1994). This claim is not based on empirical evidence but on the assumption that unbalanced lines do not exist because they are less efficient than balanced lines. The management of bottlenecks has come under increased research scrutiny in recent years. Part of this interest arises from the heavily promoted theory of constraints and drum-buffer-rope (Goldratt, 1991). Classic studying works on unbalanced serial lines include Hillier and Boling (1977), who introduced the concept of the bowl phenomenon as a description of the optimal allocation of work in serial lines. Their results show that the optimal allocation of buffers follows an (inverted) bowl shape, with more buffers allocated towards the center of the line.

Most of the researchers addressing production bottlenecks have been principally focused on managing around bottlenecks rather than managing them directly. For example, Lambrecht and Segaert (1990) studied the effect of buffers in an unbalanced serial line. Their finding suggests that as the bottleneck becomes more severe, the required buffer capacity is reduced, the reason being that the other adjacent workstations serve as buffers. The more severe the bottleneck, the smaller the throughput, but in order to protect its corresponding throughput, less inventory is needed. Chiadamrong and Limpasontipong (2002) studied unbalanced asynchronous flow line and determined the optimal buffer size either in front of or behind the bottleneck station. The preferable position of the buffer is to place towards the bottleneck station. The optimal size of the buffer in front of the bottleneck is controlled by the cost ratio of holding a buffer space in relation to revenue per unit of throughput per unit time since it is nearly full of the time while the size of the buffer behind the bottleneck should just be large enough to accommodate parts without causing line blockage.

In studying the comparison between push and pull production mechanisms, Sarker and Fitzsimmons (1989) compared the performance of pull systems with that of push systems under different operational conditions. The result suggested that the pull system is always better at work-in-process, but less efficient than the push system, especially at higher coefficients of variation. Ou and Jiang (1997) conducted an experiment via queuing models to compare the yield from push and pull control methods on production systems with unreliable machines. With the JIT pull control method, the work-in-process is controlled directly, so when the upstream machine becomes abnormal, it can be discovered sooner and the corrective action can be taken. Comparatively with the traditional push method, the work-in-process is generally larger and thus it takes longer to expose problems occurring at the upstream machine.

Yenradee (1994) has studied the performance of the push, pull and detail-scheduling system in an environment of a multi-product flow shopping having fluctuating demand, machine breakdown, and varied cycle time. The study is also concerned with customer service level, average throughput rate, and average inventory level. It was found that the pull system has satisfactory performances when the changeover and setup time are negligible. Lee (1998) examined the performance of the push and pull systems under different load (demand) conditions. Effectiveness measures monitored include job throughput, process utilization and inventory levels. Ertay (1998) used simulation to compare a pull system in a cell manufacturing system with a push system in a conventional production system in terms of economic analysis reflecting on the simplification of workflow and reduction of the setup time.

Bonney *et al.* (1999) examined the push and pull systems by means of simulation to study the effect that push and pull information flows have on system performance under a variety of conditions. Geraghty and Heavey (2004) compared two production inventory control policies: Hybrid Push/Pull and CONWIP/Pull under optimal safety stock and inventory conditions by simulated annealing. The best Hybrid Push/Pull policy under the optimal setting appeared to be CONWIP/Pull. Ozbayrak *et al.* (2004) compared push-pull strategies in terms of effects on the product costs. Activity based costing is used alongside a mathematical and simulation model to estimate the manufacturing and product cost in an automated manufacturing system. The study suggested that the pull-based control strategy has consistently given lower manufacturing costs in each scenario. The major cost differences come from lead time differences when conversion of these time-based activities to costs has resulted in lower cost figures.

To be fair on the comparison, all systems under a comparison must be compared at their best or operating with their optimal policies. Currently, most of the commercial simulation optimization algorithms are dominated by meta-heuristics since they are designed to seek global optimality and seem to have robust properties in practice (Fu, 2002). Meta-heuristic methods are global search techniques that attempt to optimize and find acceptable solutions for complex optimization problems, without requiring mathematical knowledge of the system that they are optimizing. Some prominent techniques that belong to this category include genetic algorithm, simulated annealing, and tabu search. Although the meta-heuristics require significant computation times to obtain a global solution, optimality of the final solution is not ensured because no optimality conditions can be verified. However, if the stopping criterion and the parameters of the algorithms are selected appropriately, they can be used to solve complex problems with ease. The objective of this paper is not to seek the best performance of these meta-heuristic algorithms. Rather, a structured experiment is conducted and a meta-heuristic algorithm is used to optimize our compared systems under various systems and experiment conditions.

Genetic Algorithm (GA), which is selected to be the search method in this study, is a meta-heuristic search method that uses a population of variable-length computer programs and a search strategy based on biological evolution. Among various optimization methods, GA has been widely used in recent years by many researchers to overcome the drawbacks of mathematical models (Chan and Hu, 2001). Among a number of researchers that have employed GA for searching the optimal solutions, Prasertwattana and Chiadamrong (2004) used GA to find the optimal setting in a single manufacturer and multiple retailers' case in a supply chain network. Wang *et al.* (2006) proposed an effective hybrid genetic algorithm for permutation flow shop scheduling with limit buffers. A decision probability is used to control the utilization of genetic mutation operation and local search based on problem-specific information so as to prevent the premature convergence and concentrate computing effort on promising neighbor solutions.

The scope and limitation of the study are shown as follows:

- The system under investigation is a flow line operating with a single product and limited to only one bottleneck point.
- Controllable factors of the system design are limited to buffer size in front of each machine (for the push system) or number of kanbans (for the pull system), inter-arrival time between order arrivals, bottleneck position, and level of the bottleneck severity.
- Only uncontrollable factors in the study are machine down time and its repairing time.
- The reduction of the bottleneck's operating time is set to follow the learning curve theory.

## 3. CHARACTERISTICS OF THE INVESTIGATED SYSTEM

The system under investigation is the flow shop (as shown in Figure 1 and 2). Even though undesirable, the bottleneck, which can cause line blocking and starving, is difficult to avoid. As a result, the management to alleviate the severity of the bottleneck is critical to build the firm's competitiveness. In addition, most of the researchers addressing production bottlenecks, have been principally focused on managing around bottlenecks rather than managing them directly. This study then aims to compare the system performance between the push and pull systems with a bottleneck process under their optimal designs, which include the reduction of this bottleneck severity. The performance of the system refers to how well the system generates the profit. Factors of the system design include buffer size in front of each machine (for the push system) or number of kanbans (for the pull system), inter-arrival time between order arrivals, bottleneck position, and level of the bottleneck severity.

Buffer size or number of kanbans indicates the amount of work-in-process. Inter-arrival time between order arrivals refers to an ability of the system to accommodate the amount of customer demand. Different bottleneck positions in the line affect the location that machines may block or starve incoming or processed parts. The bottleneck severity reflects on the degree of severity that the bottleneck process limits the output of the entire system. The optimal design of the system is the configuration of the line that generates the highest profit.

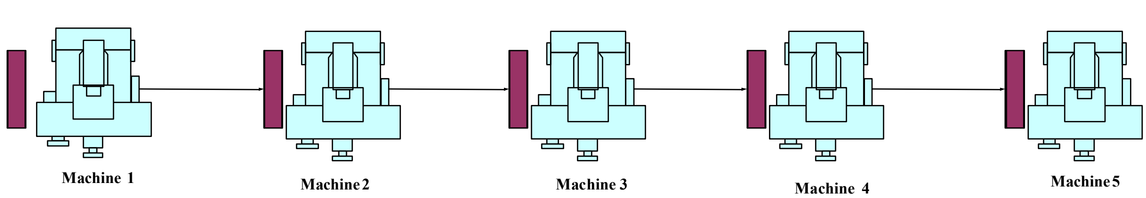


**Figure 1.** Push system's flow line

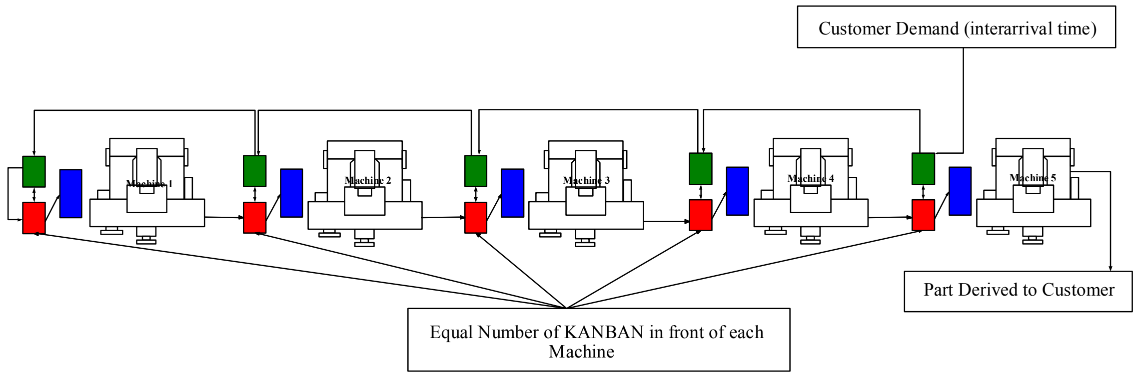


**Figure 2.** Pull system's flow line

A case study of a line consisting of five machines, where one machine is set to be the bottleneck process, is used for demonstrating the essence of our decision support tool. All machines' operating times are set to follow lognormal distribution. Buzacott and Shantikumar (1993) suggested that real workstation times exhibit positive skewness as does the lognormal distribution. In addition, the lognormal also has the useful property that both its mean and standard deviation can be varied continuously over a wide range of values. As a result, the operating time of non-bottleneck machines will follow lognormal distribution with a mean of 5 minutes and the standard variation is set at 20% of its mean. However, the initial operation time of the bottleneck process has its mean processing time to be twice longer than other non-bottleneck machines. This is due to the fact that, if the processing time of the bottleneck process appears to be longer than twice of other non-bottleneck processing time, it would make more sense and be more financially justified to buy an extra machine and run them in parallel.

For the optimal design, one may choose to reduce this severity of the bottleneck process. To be fair, an attempt to reduce this bottleneck severity must incur some expenses, otherwise the optimal setting of this factor would always suggest reducing the operation time until it is no longer the bottleneck. We assume that the bottleneck time's reduction follows the learning curve phenomenon, which is based on the fact that when a given task (i.e., bottleneck time's reduction activities) is performed repeatedly by the worker, it is gradually learned so that the time required performing it decreases with each successive unit. This phenomenon applies to any repetitive activity (Groover, 2001). As a result with a learning rate of 90% (as recommended by Smith (1989) for machining processes), the bottleneck processing time's reduction cost around 10,571 Baht is assumed to pay for every reduction step (see appendix for further calculation details). In addition, the operation time of the bottleneck process cannot be reduced shorter than those of non-bottleneck machines. So, there are maximum 94 steps that the bottleneck time can be reduced from the initial setting of 10 minutes to normal machine time of 5 minutes. Machine down time and its repair times can also be optionally set as an uncontrollable factor or noise in the experiment. In this case study, the mean time between failures and mean time to repair of each machine are set at 500 minutes and 20 minutes exponentially distributed respectively.

On completion of a process, the part proceeds to subsequent processes one at a time until it exists from the system. Due-date of each job is calculated using the total work content method with the multiplier of 4. In Blackstone *et al.* (1982), it is pointed out that this is the most rational method of assigning internally determined due-dates. As a result, when parts finish beyond their due-dates, the penalty cost would be charged.

One system may perform better at one performance measure but worse at another performance measure. As a result, it would be unfair to compare these systems based on just one performance measure and conclude that it is better. To be fair, systems should be compared under the same condition by looking at the overall performance criteria. This is the reason why the push and pull systems should be compared under the basis of economic consideration or the profit generated from the system since it can present overall criteria in judging the whole performance. The simulation experiment is set with 5 replications for controlling the accuracy of its results. Each replication is run for 115,200 minutes equal to the study of one-year period. This is to make sure that the obtained results can achieve the accuracy of the profit figures within 5% of the mean value under 95% confidence level and this replication length is long enough to compensate any initial bias and minimize dependency between replications.

## 4. GENETIC ALGORITHM'S PROCEDURES

In this section, we present the procedure of Genetic Algorithm (GA) to solve the design problem. Five features should be considered for a GA, namely. setting searching boundary, initializing population, fitness function, genetic operators, and a set of input parameters.

### 4.1 Setting Lower Bound and Upper Bound of the Solution

The lower and upper bound of each control variable is set to limit the computational time from GA. However, the searching boundary for each decision variable must be large enough to ensure that the optimal solution will fall inside the boundary. Searching boundary of our selected decision variables needs to be defined where the buffer size or number of kanbans is between 1 unit to 100 units; the order inter-arrival time is between 0 minute to 180 minutes and the number of bottleneck time's reduction step ($N$) is between 1 step to 94 steps. In all, the length of the chromosome is 35 bits. We need to do this process 5 times. Each time is at each assigned position of the bottleneck process (machine 1 to machine 5).

### 4.2 Initializing Population

GA starts with an initial set of random solution called population. In this study, the population is set to contain 30 chromosomes. We use a random number generator to generate the initial population $P(k=0)$ in form of binary numbers, where $k$ is a generation index.

### 4.3 Fitness Function

Each chromosome is assigned a fitness value. The fitness of a chromosome represents the profit generated from simulating both systems at each bottleneck position using the values of the other three control variables stored in the chromosome.

### 4.4 Genetic Operators

The roulette wheel approach is chosen as a method to select the chromosome and make a mating pool for reproduction. The roulette wheel approach belongs to the fitness proportion selection and can select a new population with respect to the probability distribution based on fitness values. Having selected the operation, a mating pool is formed. The next step is to do a crossover operation. Crossover operation used in this study is three random cut-points, which exchange the right parts of two parents to generate an offspring. Then, the mutation operator flips a bit in a chromosome by the random method. After the first generation has completed, the new population size will be collected. Then, the process repeats itself until the generation reaches the stopping criterion when the best population has not improved in the last $t$ generations or reaches termination ($k_{max}$).

### 4.5 Input Parameters

The GA parameters used in this study can be shown as follows:

- Number of chromosomes in the population = 30
- Probability of crossover ($P_c$) = 1
- Probability of mutation ($P_m$) = 0.1
- Number of generations ($k_{max}$) = 10,000
- Stopping condition: when the solution does not improve further for the last 15 generations or number of iteration reaches $k_{max}$.

It is noticed that these parameters are selected according to De Jong's (1975) suggestion: "… good GA performance requires the choice of a high crossover probability, a low mutation probability (inversely proportional to the population size)."

## 5. PROFIT MODEL

The profit model is constructed and used to convert the performance of each design into monetary terms. Table 1 presents the cost structure used in the experiment.

$$Profit = Revenue - Total\ costs \tag{1}$$

$$Revenue = Number\ of\ finished\ products\ x\ Unit\ price \tag{2}$$

$$Total\ costs = \sum_{i=1}^{m} O_i + Rm + \sum_{i=1}^{m} H_i + \sum_{i=1}^{m} I_i + Ls + Lp + Br \tag{3}$$

where:
$O_i$ = total operating cost of machine $i$ (Baht)
$Rm$ = total raw material cost (Baht)
$H_i$ = total part holding cost in a queue in front of machine $i$ (Baht)
$I_i$ = total idle cost for machine $i$ (Baht)
$Ls$ = total lost sale cost (Baht)
$Lp$ = total late penalty cost (Baht)
$Br$ = total bottleneck reduction cost (Baht)
$m$ = total number of machines

Total operating cost

$$O_i = (OT_i \times n_i) \times Oc \tag{4}$$

where:
$O_i$ = total operating cost of machine $i$ (Baht)
$OT_i$ = average operating time of machine $i$ (minutes)
$n_i$ = number of parts operated by machine $i$
$Oc$ = machine utility cost per minute (Baht)

Total raw material cost

$$Rm = F \times Rc \tag{5}$$

where:
$Rm$ = total raw material cost (Baht)
$F$ = number of raw materials consumed
$Rc$ = raw material cost per unit (Baht/unit)

Total holding cost

$$H_i = \frac{QT_i}{t} \times Uc \times C_{TH} \quad (6)$$

where:
$H_i$ = total part holding cost in a queue in front of machine $i$ (Baht)
$QT_i$ = total part waiting time in a queue in front of machine $i$ (minutes)
$t$ = one year replication length (minutes)
$Uc$ = unit cost (Baht/unit)
$C_{TH}$ = cost of capital due to part holding (percent/year)

Total machine idle cost

$$I_i = [(1-U_i)\times t + IT_i] \times E_m \times \left(\frac{D \times M_c \times m}{t}\right) \times C_{TI} \quad (7)$$

where:
$I_i$ = total idle cost of machine $i$ (Baht)
$U$ = utilization of machine $i$ (percent)
$IT_i$ = total blocking time of machine $i$ (minutes)
$E_m$ = machine efficiency (assumed equal for all machines)
$D$ = depreciation rate per year (percent/year)
$M_c$ = machine investment costs (Baht)
$C_{TI}$ = cost of capital due to machine idleness (percent/year)

Total machine repairing cost

$$RR_i = RT_i \times RP_c \quad (8)$$

where:
$RR_i$ = total repairing cost of machine $i$ (Baht)
$RT_i$ = total repair time of machine $i$ (minutes)
$RP_c$ = machine repairing cost per minute (Baht/minute)

Total lost sales cost

$$Ls = OP \times LS_c \quad (9)$$

where:
$Ls$ = total lost sales cost (Baht)
$OP$ = total overflowed units from the system (units)
$LS_c$ = lost sales cost per unit (Baht/unit)

Total late penalty cost

$$Lp = LT \times LP_c \quad (10)$$

where:
$Lp$ = total late penalty cost (Baht)
$LT$ = total late time (minutes)
$LP_c$ = late penalty cost per minute (Baht/minute)

Total bottleneck severity reduction cost

$$Br = Bc \times N \quad (11)$$

where:
$Br$ = total bottleneck severity reduction cost (Baht)
$N$ = bottleneck time's reduction step
$Bc$ = bottleneck time's reduction cost per reduction step

**Table 1.** Cost structure

| | |
|---|---|
| Selling price per unit ($P$) | 350 Baht/unit |
| Raw material cost per unit ($R_c$) | 50 Baht/unit |
| Machine utility cost per hour ($O_c$) | 90 Baht/hour |
| Part unit cost ($U_c$) | 150 Baht/unit |
| Machine efficiency ($E_m$) | 90% |
| Depreciation rate ($D$) | 20% per year |
| Cost of capital due to part holding ($C_{TH}$) | 480% per year |
| Cost of capital due to machine idleness ($C_{TI}$) | 30% per year |
| Machine investment cost ($M_c$) | 1,000,000 Baht |
| Bottleneck time's reduction cost ($B_c$) | 10,571 Baht/reduction step |
| Lost sales cost ($LS_c$) | 50 Baht/unit |
| Late penalty cost ($LP_c$) | 2 Baht/minute |
| Machine repairing cost per minute ($RP_c$) | 2.5 Baht/minute |
| **Remark: 1 US $ ≈ 40 Baht** | |

## 6. AN ILLUSTRATIVE EXAMPLE

With the goal of determining how the bottleneck position affects the performance of the system, we have tested the models under various bottleneck positions (from 1st machine to 5th machine). Table 2 and 3 summarize the best parameter setting policies for the push and pull systems at each bottleneck position.

**Table 2.** Summary of the best setting policy from each bottleneck position for the push system

| Bottleneck position | Average maximum profit from five replications (Baht) | Buffer Size (units) | Degree N | Inter arrival time (min) |
|---|---|---|---|---|
| 1 | 3,542,318 | 22 | 33 | 6.693 |
| 2 | 3,555,963 | 58 | 43 | 6.697 |
| 3* | 3,588,403* | 59 | 43 | 6.747 |
| 4 | 3,545,976 | 72 | 40 | 6.879 |
| 5 | 3,496,519 | 10 | 44 | 6.888 |

* Best parameter setting policy for the push system

**Table 3.** Summary of the best setting policy from each bottleneck position for the pull system

| Bottleneck position | Average maximum profit from five replications (Baht) | Number of kanbans (units) | Degree N | Inter arrival time (min) |
|---|---|---|---|---|
| 1* | 4,403,289* | 20 | 53 | 5.724 |
| 2 | 4,325,692 | 30 | 59 | 5.753 |
| 3 | 4,308,628 | 20 | 53 | 5.725 |
| 4 | 4,253,609 | 17 | 42 | 6.057 |
| 5 | 4,124,378 | 13 | 84 | 5.548 |

* Best parameter setting policy for the pull system

Referring to the best position for placing the bottleneck, for the push system, the best bottleneck position is at the 3rd machine (at the middle of the line). If the bottleneck is located earlier in the line, the receiving amount of customer order would be limited by its capacity, and causing high lost sales cost. However, if the bottleneck is located later in the line, higher inventory would be built up along the line, especially in front of the bottleneck process and this causes too high holding cost. This outcome, where the best position of the bottleneck is at the middle of the line, reflects on the economic consideration's view point that is to trade off between the lost sales cost and inventory holding cost. For the pull system, the best bottleneck position is at the 1st machine. With the nature of the pull system where the level of the system's inventory is controlled by the number of kanbans, which are initially assigned to each stage, the position of the bottleneck process shows to have little effect to the holding cost. Therefore, the pull system would prefer to have the bottleneck placing further away from the last station in the line (which is the first station to be pulled). In this way, the bottleneck would not block the incoming orders and would not cause too high lost sales cost.

In order to investigate the impact of the push and pull mechanisms on the system under economic consideration, we manage to compare the profit, all related costs and some interested performance measures (i.e., customer lead time and number of units produced) as presented in Table 4 and Figure 3. In fact, the paired t-test comparison has also been tested to find the significant difference between the two systems at their optimal policies. From the test, it can be concluded that all costs except the machine repairing cost are statistically shown to be significantly different at 95% confidence level. This is understandable since each machine from both systems is randomly set to break down at the same timing parameter so there should not be too much difference between them. At the optimal design, it is also found that the pull system can generate a higher profit (22.71% higher in profit), bring in more revenue (17.35% higher in revenue), accommodate higher customer demand (17.35% higher in units produced) and respond faster to the customer order (44% shorter in lead time).

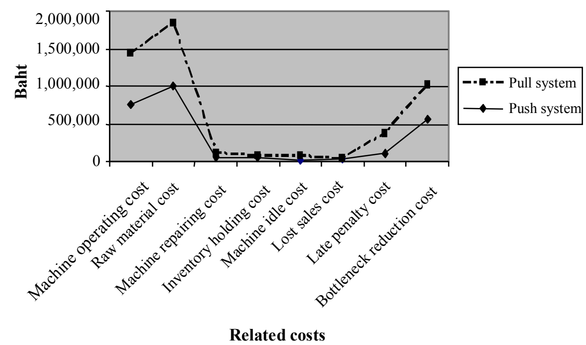


**Figure 3.** Cost comparison between the push and pull systems at their optimal designs

Regarding the costs, the push system shows operation with the overall lower cost (9.24% lower in total costs). It can operate cheaper from the machine operation, raw material, lost sales, inventory holding and bottleneck time's reduction. Lower machine operation, raw material and lost sales costs of the push system are due to the fact that the pull system, at its optimal design, operates with a higher demand level (the pull system's order inter-arrival time of 5.724 minutes as compared to

**Table 4.** Profit, revenue and cost comparison between the push and pull systems at their optimal designs

| | Pull system | Push system | %Differences |
|---|---|---|---|
| | (Baht) | (Baht) | % increase from the push system |
| Profit | 4,403,289 | 3,588,403 | 22.71 |
| Revenue | 6,992,300 | 5,958,330 | 17.35 |
| Total costs | 2,589,011 | 2,369,927 | 9.24 |
| - Machine operating cost | 762,110 | 679,138 | 12.22 |
| - Raw material cost | 998,180 | 852,020 | 17.15 |
| - Machine repairing cost | 56,754 | 52,275 | 8.57 |
| - Inventory holding cost | 59,437 | 5,104 | 1,064.52 |
| - Machine idle cost | 21,194 | 55,678 | -61.93 |
| - Lost sales cost | 29,750 | 0 | |
| - Late penalty cost | 101,356 | 271,186 | -62.62 |
| - Bottleneck time's reduction cost | 560,230 | 454,526 | 23.26 |
| Other interested performance measures | | | |
| - Customer lead time (minutes)* | 42 | 75 | -44 |
| - Number of units produced (units) | 19,978 | 17,024 | 17.35 |

* time from an order arrival till the time that the order has been completed

6.747 minutes of the push system). This definitely causes this system to consume a higher amount of raw materials, longer machine operation time and perhaps some orders might be lost due to the overflowed order from the system. Unlike the push system, the pull system at its optimal design, is set to hold 20 kanbans between stages. A higher holding cost needs to be paid for this amount of inventory whether or not there is customer demand whereas the majority inventory of the push system (especially in front of the bottleneck station) would only appear when there is customer demand greater than the capacity of the bottleneck process.

However, the pull system can operate cheaper from the machine idle cost and late penalty cost. Lower machine idle cost of the pull system can be explained by the fact that the pull system is operating with a higher demand level as discussed previously. Similarly, lower late penalty cost of the pull system presents the fact that the pull system can operate with a shorter lead time. By keeping a number of kanbans between succeeding stations, the pull system is shown to respond to the demand more quickly. However, it has to pay the price by having a higher inventory holding cost as a consequence.

According to the above-mentioned results, one may see that both systems are compared based purely on the cost. We would conclude that the push system is superior. However, if the profit criterion, where both revenue and costs are simultaneously considered, is used for comparison, the result has proven to be different. As a result, as the normal aim of firms is to maximize their wealth, the judgment based on the profit would be more critical. Nevertheless, this outcome is based on one particular system characteristic and cost structure and may not be generalized to other cases. That is why a decision support tool, in which both system characteristics and the cost structures can be easily modified to match with each condition, is required.

## 7. CHARACTERISTICS OF THE DECISION SUPPORT TOOL

The tool has been developed using ARENA version 9 linked with Visual basic editor for creating input windows for all system and GA parameters, cost structure, result windows and genetic operators. Figures 4 and 5 show parameter inputs and result windows respectively.

The interaction between the simulation and genetic operators is presented in Figure 6. The tool starts from inputting the system's characteristics, all relevant costs and GA parameters including selected controllable factors and searching and stopping conditions. Then, the systems (both push and pull mechanisms) are simulated and the interested observations are collected in order to convert into cost via the profit model. Next, the result is sent to the genetic operators to evaluate its fitness and generate the next offspring until the stopping criteria is reached as described in the section of Genetic Algorithm's procedure.

Therefore, the tool can be used to assist in managerial decision making by allowing users to define their own system characteristics including the specific location and time of the bottleneck process as well as their firms' cost structure. It is very easy to use and could be a practical tool in a real industrial context. The obtained results are able to reflect on the firms' actual outcomes. Moreover, the tool's ability to determine the optimal design can help decision-makers to evaluate their systems before making the final decision. An example of decisions to be made would be whether to implement the push or pull strategies in each condition and the best settings of their system parameters including an appropriate buffer size or number of kanbans, the best bottleneck position and judgment on the reduction of the bottleneck severity.

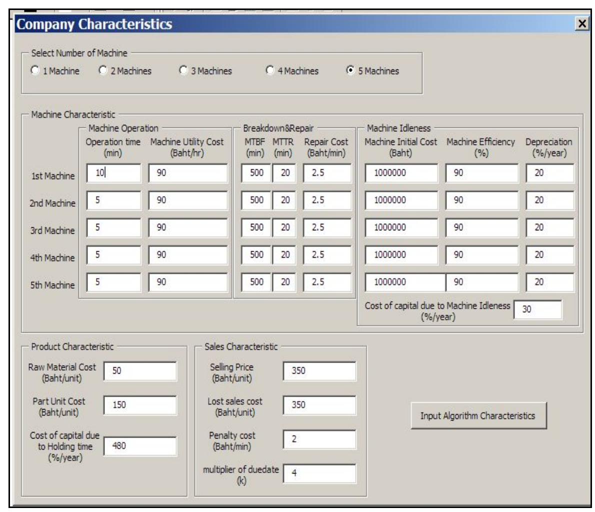


**Figure 4.** Input window of systems' characteristics and cost structure

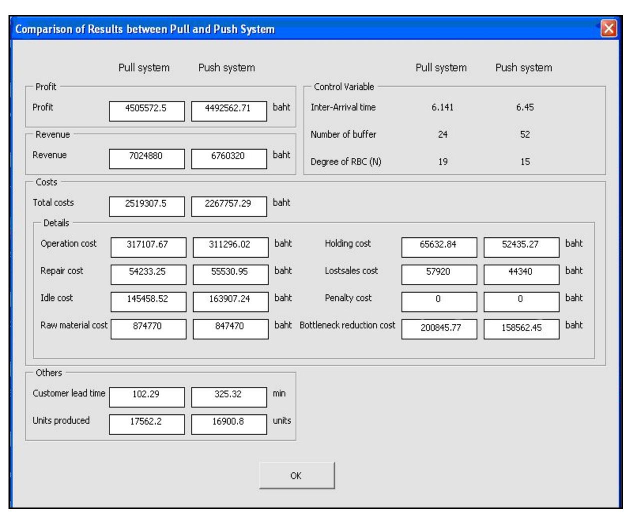


**Figure 5.** Result window recommending the best operating policy

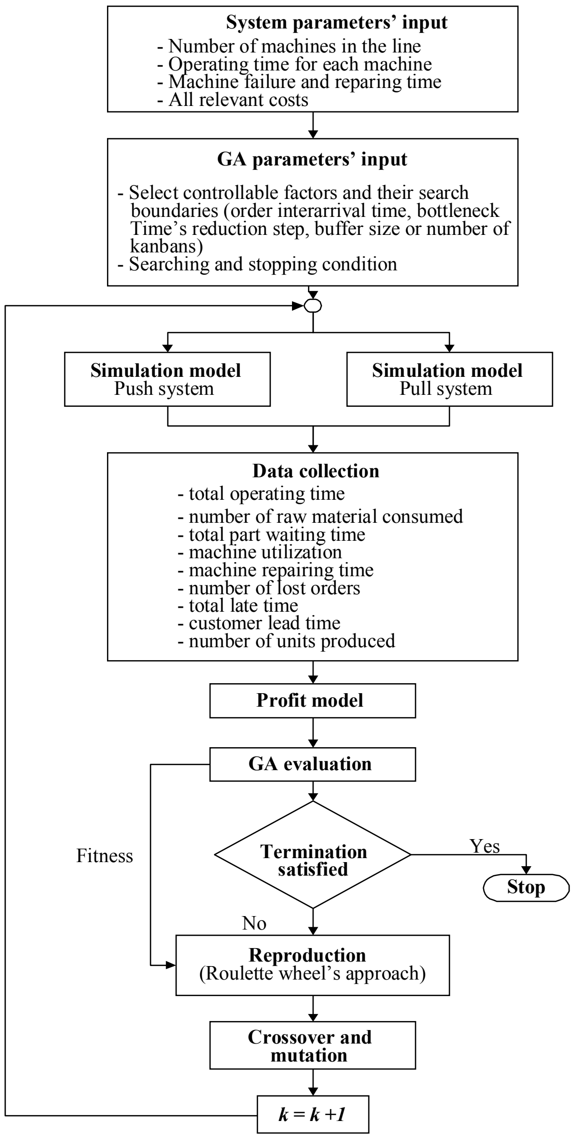


**Figure 6.** Interaction between simulation and optimization

## 8. CONCLUSIONS

Using simulation combined with genetic algorithm, the effects of manufacturing planning and control strategies, namely push and pull on the profit, are examined. Positioning of the bottleneck process, size of buffer or assigned number of kanbans, system ability to accommodate customer order and the level of bottleneck severity are system parameters for judging the optimal design. It is important to understand the effects from setting these system parameters, and to manage them in the context of maximizing the firms' profit. Any action that takes place in the system that either contributes to the manufacturing or not, is associated to with one of our costs. By applying a planning and control strategy, these actions are transformed into monetary terms. Therefore, if the planning and control strategy does not have the ability to create value added activities and streamlined manufacturing, which would lead to minimization of any form of waste, all the wasted actions will be translated into cost.

The results of the illustrative example reveal that the manufacturing planning and control strategies play an important role on the level of manufacturing revenue and costs of a system. We have found that the pull system at the optimal design gives a superior performance on the profit. Even though, the push system at its optimal design slightly yields low costs, the pull system can bring in much higher revenue as a result of its ability to accommodate a higher level of customer demand as well as a shorter lead time. It is worth noting that these results are based on just one set of cost structures. When the cost structure is changed, the conclusion made from the analysis may also be changed. As a result, it would be incorrect to draw too many conclusions from this study. However, the proposed methodology and evaluation can be used as a guideline for firms in setting their suitable manufacturing planning and control strategy and highlighting the effects from setting system parameters to the overall system performance.

With the goal of creating a decision support tool, an additional function has been added so that system designers and users can adjust the system requirements matching with their own circumstances. The forms for user input allow users to fully define the characteristics of their manufacturing systems and associated costs. The outcomes would definitely present a better understanding of each system and make it possible to evaluate both systems fairly. The benefits of the tool also extend beyond just simulating manufacturing systems. By performing a comparative study on the push and pull strategies at their optimal designs, the strength and weaknesses of each system are revealed. Understanding the strength and weaknesses brings deeper knowledge to the nature of push and pull strategies. A collection of this knowledge will fuel the advancements of manufacturing system designs. However, there are also some limitations of this tool and additional work is needed to enhance the ability of the tool to accommodate other system design parameters. In addition, the current study represents an initial study with respect to GA optimization, the comparison with the results obtained from other meta-heuristic search methods would help to find the best performance of the interested systems.

## APPENDIX

### Learning Curve Phenomenon

According to the learning curve theory (*see* Smith (1989) and Groover (2001)), there is a constant learning rate that applies to a given task. Whatever the learning rate, its effect is most identifiable every time the number of units doubles. Assuming a learning rate of 90%, the time to do the second time is 90% of that for the first time; the time to do the fourth time is 90% of that for the second; and so forth. Every time the number of units doubles, the task time per unit has been reduced to 90% of its previous value. Between these points, the unit task times gradually decrease. We can calculate the expected time for the $N^{th}$ task unit by means of the following equation;

$$T_N = T_1(N)^m \tag{12}$$

Where
$T_N$ = task time for $N^{th}$ unit of work
$T_1$ = task time for the first work unit
$N$ = the number of task times
$m$ = an exponent that depends on the learning rate

The value of $m$ can be determined as follows:

$$m = \frac{ln(LR)}{ln(2)} \tag{13}$$

where
$LR$ = learning rate, expressed as a decimal fraction

Knowing that $T_1$ or the initial operation time of the bottleneck process is set at 10 minutes and it can be reduced not less that 5 minutes ($T_N$) with the learning rate of 90% ($m$ = -0.152 obtained from equation 13), substituting these values to equation 12 yields the value of $N$ equal to 94.60. As a result, there are maximum 94.60 bottleneck time's reduction steps that we can perform to the bottleneck process until it reaches the operation time of non-bottleneck operations (5 minutes). Since the machine investment cost is set at 1,000,000 Baht in the case study, the bottleneck reduction cost per step ($Bc$) then can be calculated as follows:

*Bc* = *Machine investment cost (Mc)/Possible number of bottleneck reduction steps (N)*
*Bc* = 1,000,000 / 94.6 = 10,571 Baht/step

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