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A SIMULATION APPROACH TO EVALUATING MANUFACTURING SYSTEM PERFORMANCE

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Abstract

Since testing wide range of management decision in real-world production is absolutely impossible, discrete-event simulation has often been adopted to evaluate the manufacturing system performance. Performance of various layout alternatives can be studied using simulation. In this paper there are presented reasons to use simulation in order to evaluate manufacturing system performance. Paper presents a simulation approach to assessing the impact of management decision on a production process and the associated impact on costs and on potential gain.

Keywords
simulation, system performance, manufacturing.

Introduction

Analysis of large and complex stochastic systems is a difficult task due to the complexities that arise when randomness is embedded within a system. Unfortunately, unexplained randomness is a common and unavoidable characteristic among real-world systems. A simulation modelling as an evaluative tool for stochastic systems has facilitated the ability to obtain performance measure estimates under any given system configuration [1]. Simulation is a very powerful tool often used in the design phase of manufacturing systems. Performance of various layout alternatives can be studied using simulation. Performance measurement is indispensable to manufacturing enterprise. If the effective efficiency of an activity cannot be measured, it could not be properly controlled. While mechanistic or physical measurements could be made extremely accurately due to advances in metrology, the measurement of manufacturing performance remains an unsettled subject due to the diverse and multi-dimensional nature of manufacturing [2].

Simulation is an important area of investigation; the clarification of the different types of simulation with respect to their areas of specialty for providing solutions to industry is necessery. There are various ways of classifying a simulation. First, it can be classiffed in terms of the simulation approach, that is, the underlying simulation engine. There are two main approaches to simulation, namely, discrete and continuous. Within these approaches, distinct types exist. Monte-Carlo simulation, discrete-time simulation or time slicing [3], and discrete-event simulation [4] are all forms of discrete simulation. Continuous simulations are approximated by using a constant time step, with smaller time steps providing a greater degree of granularity. Other way that simulation can be classiffed in terms of its application area. Discrete-time simulations are typically used for economic models, whereas discrete-event simulations are widely used in management science/operational research, that is, mainly manufacturing systems, computer systems, business, military and public policy applications [5]. In the main, these models are used for statistical experimentation. Basically the main production operations in discrete manufacturing, i.e., the production of engines, chips on silicon wafers or printed circuit boards are considered. Usually, these operations are organized in a job shop or flow shop manner. Complex job shops are characterized in [6]:

– a large number of products with an over time changing,
– product mix,
– sequence-dependent set-up times,
– m.b. makespan,
– unrelated parallel machines,
– a mix of different process types, including batch processes (a batch is defined as a temporary collection of lots with the aim to process them at the same time on the same machine),
– different types of internal and external disturbances,
– re-entrant process flows due to very expensive machinery.

Once a model is developed, it can be used for statistical experimentation; that is, long simulation runs, possibly replicated a number of times, in order to achieve a result that is sufficiently accurate for the purposes of the study that is being undertaken. The benefits of using simulation for the analysis of manufacturing systems is well established. Numerous applications of simulation have been published on plant layout and utilization, testing of priority rules and inventory analysis. A recent simulation survey shows a high level of satisfaction for those using simulation, however the same survey shows concerns over data definition and speed of model building [7]. Simulation study is very helpful to analyze the performance of complex system. Such a system does not lend itself to be modeled as a product-form queuing network, and thus it is often analyzed using simulation in practice [8]. Managers and engineers who are interested in finding a quick answer for the system performance under some changes in product mix or system configuration often favor alternative method providing an approximate answer. The analyst does, after verification and validation of a simulation model, a set of simulation experiments. The experimentation with simulation model, aided by a computer, allows examining the variants of system's behaviour in a longer time period and in assumed conditions. New knowledge gained through such simulation experimenting is used for the optimization of a real (conceptual) system [9]:

Overview of a simulation study:

– Understand the system;
– Be clear about the goals;
– Formulate the model representation;
– Translate into modeling software;
– Verify "program";
– Validate model;
– Design experiments;
– Make runs;
– Analyze, get insight, document results;

Literature review and problem background

A large number of papers have been published on simulation and performance evaluation, in recent times.

In [8] an approximation approach is proposed for analyzing the performance of the re-entrant manufacturing system subject to machine failures and production loss due to scrapping of the WIP (work-in-processes). The model and its solution methodology in this paper by extending the earlier works are the results of the efforts to provide a practical and reasonable alternative to the real-world managers for an approximate performance evaluation of one of the most complicated manufacturing systems.

A multi-item MRP simulation model was developed in [10] develop and design experiments to determine the effects of factors such as forecast errors, process variability and updating on key performance measures.

In [11] authors conducted a simulation study to examine two dimensions of forecast error – standard deviation and bias. They found that standard deviation is relatively less important in terms of the magnitude of the total cost impact, which includes inventory carrying cost, setup cost and enditem shortage cost.

In [12] there is conducted a series of experiments to investigate the effects of forecast bias and demand uncertainty in a batch production environment.

Authors in [13] reviewed important parameters which have an impact on the effectiveness of MRP systems.

The aim of study in [14] was to find optimal lot sizes, in order to decrease the manufacturing lead time and to increase the production and the utilisation of resources. Thus, there was noted according to the results presented in this article that the size of lots has a very important effect on the performances of the shop.

Simulation experiments are carried out to test the dispatching rules. Authors in [15] and [16] Kumar showed that a good dispatching policy significantly improves the performance. In [17] there is proposed a new class of dispatching rules (fluctuation smoothing policy for mean cycle time, fluctuation smoothing policy for variance of cycle time,) for minimizing the mean cycle time and for minimizing the variance of cycle time. Since testing priority rules in real-world production is absolutely impossible, discrete-event simulation has often been adopted to evaluate the performance of dispatching rules for rule selection [18]. In [19] there is considered a serial multi stage production system in which products travel sequentially from stage 1 to stage n. After each of the processing stations, one of three inspection options can be chosen: no inspection, full inspection, or sampling inspection. A fusion between a discrete event simulation to model the multi-stage process subject to inspection and to calculate the resulting inspection costs, and an Evolutionary Algorithm to optimize the inspection strategies, is suggested. In [5] author presents a model of simulation project quality. To describe simulation quality, three quality concepts and their relationship are used: the quality of the content, the quality of the process, and the quality of the outcome. There is a clear link between these concepts and the ideas of validity, credibility, and acceptability.

Manufacturing measures are not new as they have been around ever since production functions exist. However, the emphasis was different in different era and this shows the evolutionary nature of performance measurement as depicted in Fig. 1 [2].

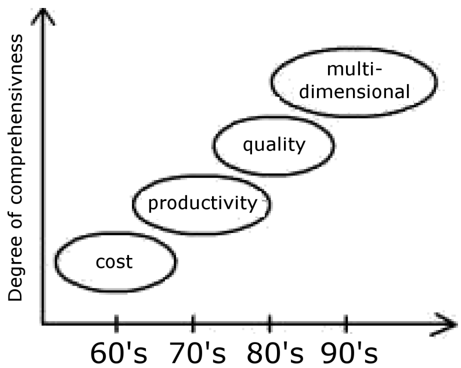

Fig. 1. Evolution of performance measures.

In paper [20] authors translate an enterprise's mission into a comprehensive set of performance measures that provides the framework for a strategic measurement and management. It is now generally accepted that it is necessary to measure all kinds of performance indicators, such as cost, speed, dependability etc. The basic performance measures in the analysis of production systems are the throughput and the average work-in-process or equivalently the average production time.

In our paper following performance measures for manufacturing system are in interest:
- Wait time in system;
- Work-in-progress (WIP) in system;
- Lengths of queues;
- System productivity;
- Costs depending on taking up phisical space;
- Costs depending on delay in execution of order.

In order to analyze these performance measures there are several formulas in simulation modeling to obtain basic parameters:

Average waiting time of parts in queue:

$$\frac{\sum\limits_{i=1}^{N} WQ_i}{N},$$

N = no. of parts completing queue wait, WQ_i = waiting time in queue of i-th part.

Maximum waiting time of parts in queue:

$$\max_{i=1,\ldots,N} WQ_i.$$

Time-average number of parts in queue:

$$\frac{\int\limits_0^{T_0} Q(t)\,dt}{T_0},$$

$Q(t)$ = number of parts in queue at time t, T_0 – period of simulation.

Maximum number of parts in queue:

$$\max_{0\le t\le N} Q(t).$$

Average and *maximum total time in system* of parts (*cycle time*):

$$\frac{\sum\limits_{i=1}^{P} TS_i}{P}, \qquad \max_{i=1,\ldots,P} TS_i$$

TS_i = time in system of part i.

Utilization of the machine (proportion of time busy):

$$\frac{\int\limits_0^{T_0} B(t)\,dt}{T_0},$$

$$B(t) = \begin{cases} 1 & \text{if the machine is busy at time } t, \\ 0 & \text{if the machine is idle at time } t. \end{cases}$$

Problem formulation

The following assumptions will be made:
1. The manufacturing system can produce i different products at the same time. A technological itinerary is assigned to each product.
2. Customers demands enter the manufacturing system according to the Poisson process (infinite population).

3. After an individual part arrives at the system, it goes directly to a manufacturing station for its first manufacturing operation. If there are parts for being processed, it queues up because of limited production resources.
4. After completion of processing at a manufacturing station, it goes to another manufacturing station to be processed in its routing sequence of manufacturing operations.
5. The product leaves the system in its finished form from the last node of the queueing network.
6. Each part has characteristics (e.g. number of pages, number of copies), which are statistically independent of other parts.
7. The processing time (general distribution) at each workstation is independent of preceding processing times.
8. All machines at each work station work without breaking down.
9. All input buffers are finite (different capacities before different work stations).
10. Transfer time between work stations is omitted (transfer times are negligible small comapred to processing times).
11. The queuing network is in a steady state.

Now we can formulate the following theoretical problem:

For known

– a set of product types $\{i\}$ and rate of arrival of customer demands for each kind of product λ_i , $i = 1, 2, ...i*$,
– a set of workstations $\{j\}$ at manufacturing system and rate of servicing for each workstation $\mu_j = m_i/\widetilde{\tau}_j$, where: m_j is a number of servers at workstation j, operating in parallel, $\widetilde{\tau}_j$ is average time of servicing at workstation j
– matrix of workstation utilization $R = \|r(ij)\|$, where $r(ij) = 0, 1, 2....$, is a number of visits the workstation j by product type i
– costs coefficients:
  a a profit coefficient associated with the production rate,
  c_j a cost coefficient associated with the buffer space for the buffer j,
  d_j a cost coefficient associated with average inventory for the buffer j,
  $\alpha_i \widetilde{t}_i$ the cost of system time for product kind i (work in process), $\widetilde{t}_i$ *is lead time of product i*,
  β_j, γ_j the cost of work and idle time of workstation j correspondingly,
  T_0 period of optimization.

It is necessary to determine

– b_j – buffer capacity at workstation j,

– $pr_j \in$ – servicing discipline at each workstation $n_j \in N$; $pr_j \in$ {FIFO – first in first out, EDD – earliest due date, LOR – least operations remaining, MOR – most operations remaining, SPT – shortest processing time, LPT – longest processing time},

– ρ_j – utilization of each workstation $j = 1, ...j*$,

where b_j and pr_j are decision parameters but ρ_j is computable variable.

Providing

minimum of complex criterion function for period of optimisation T_0.

Output system parameters:

– $\eta_{i,j}$ an average arrival rate of a customers' jobs for product j at workstation i,

– $\sigma a^2_{i,j}$ a standard deviation of a customers' jobs inter arrival time for product i at workstation j,

– σs^2_i a standard deviation of a technological operation duration at workstation j,

– Lq_j is a queue length (average number of jobs at buffer j).

Developed below criterion function follows an example in [21]. In mathematical terms, our problem could be stated as follows:

$$\zeta = a \cdot P_i - \sum_{j=1}^{k} (b_j c_j + Lq_j d_j) + \sum_{i=1}^{l} \lambda_i \widetilde{t}_i \alpha_i + \\ - \sum_{j=1}^{k} m_j(\rho_j \beta_j + (1 - \rho_j)\gamma_j) \to \max_{T_0}, \tag{1}$$

where P_i is the production rate of a system.

Although the production rate P is a function of machines and their reliability, we vary only buffer sizes and priority rules. The first term of the Eq. (1) can be seen as the total revenue of the production system; while the other three items together can be interpreted as the total cost of the production system. The c_j coefficient expresses a cost of space necessary for storing maximum level of work-in-progress and d_j coefficient expresses a cost of a working capital allocated in queues, α_i coefficient expresses a cost of work in process in the system. Last component of criterion function expresses a cost of work and idle time of workstations.

Case study of Commercial Offset Printing System

A typical commercial printing facility will serve as a test bench for the analysis. ARENA simulation package from Rockwell Software (version 9.0) was used for modeling the manufacturing system. The purpose of the simulation was to analyze how changing priority rules influences output parameters taking into account various machines utilization levels. Since testing priority rules in real-world production is absolutely impossible, discrete-event simulation has often been adopted to evaluate the performance of dispatching rules for rule selection. A dispatching rule is used to select the next job to be processed from a set of jobs awaiting service at a facility that becomes free. The dificulty of the choice of a dispatching rule arises from the fact that there are $n!$ ways of sequencing n jobs waiting in the queue at a particular facility and the shop-floor conditions elsewhere in the shop may influence the optimal sequence of jobs at the present facility. There are many stochastic components in the simulation model that are briefly discussed here. In general, the production facility is extensively automated, but not deterministic due to the nature of the product and the involvement of human operators. Random probability distributions are used to represent processing times. Randomly generated product characteristics (e.g. number of pages, number of copies) are another source of uncertainty that influences the behavior of the system.

Simulating assumptions:

There is a 9 workstations (RIP, CTP, Offset printing machine, Reversing, Drying, Folding, 3-knife trimmer, Sticking cover, Sewing cover), all of them have set processing time μ_j randomly distributed according to an general distribution (mean setup times and standard deviations of all operations are data are from real world machines specifications).

Model is characterized by following parameters:

1. Five priority rules *pr* are analyzed (to compare also FIFO rule is analyzed):
   $pr \in \{FIFO,\ EDD,\ LOR,\ MOR,\ SPT,\ LPT\}$.

2. Input buffer capacity b_j respectively for workstation j (RIP station has infinite buffer capacity):
   a. 81, 126*, 108, 81, 81, 108 (L),
   b. 90, 140*, 120, 90, 90, 120 (M),
   c. 99, 154*, 132, 99, 99, 132 (H).
   In case ‘b’ optimal buffer’s capacity are found in [22]. Capacity in case ‘a’ is 10% smaller than optimal and case ‘c’ is 10% greater. * common buffer for printing, drying and reversing.

3. Workstation utilization ρ_j is examined on the following levels (in erlang notation):
   0.55e, 0.6e, 0.65e, 0.7e, 0.75e, 0.8e, 0.85e, 0.9e, 0.95e, 0.99e.

4. Three types of product exist in system:
   a. Leaflet $i = 1$,
   b. Brochure $i = 2$,
   c. Book $i = 3$.

5. Analyzed performance output parameters:
   a. Profit function ζ (1),
   b. Wait time in system (for each product type class independently),
   c. Work-in-progress (WIP) in system (for each product type class independently),
   d. Length of queue before printing machine.
6. Simulation runs parameters were selected in order to assure reliable results:
   a. warm-up time is 1 day,
   b. replication length is 100 days,
   c. number of replications is 7.

The experiment design is described in the following section followed by a discussion of results. Customers orders’ arrival patterns are exponential. Bounds for orders arrival rate λ_i for the leaflet and brochure are from 10 to 20 jobs per time unit and for the book are from 15 to 25 per time unit. Input parameters (stochastic values of number of copies, number of pages, format type, cover type) for each type of product are converted and number of sheets for each order is calculated. In this case, it is established that the performance measures of the system are sensitive to priority discipline in terms of work-in-process inventory, work centre utilization, queue time, setup time, process time, etc. Consequently, modification of the priority strategy is capable of altering the production system functioning. Therefore, it is important to know the effects of the priority discipline problem on production and optimal configuration of the studied system.

Since many rules are tested for each decision problem in this study, all combinations of the rules in all workstations may not be included in the experiments because of an excessive computational burden. In commercial offset printing system, the bottleneck workstation is the offset printing machines. In this situation experiments was executed with changing priority rules only before this workstation for all utilization levels and buffer capacities. This will provide 1260 ($3 \cdot 10 \cdot 6 \cdot 7 = 3$ buffers levels, 10 utilization levels, 6 priority rules and 7 replication for each variant) simulation runs. For these parameters sensibility analysis was performed according to DOE

(Design of Experiments) methodology [23]. Results of ANOVA (Analysis of Variance) at 0.05 confidence level are shown at Table 1. From the study appears that buffer's capacities (B) have little influence on profit in comparison with assigned priority rule (P) and workload (U) (the biggest spread between F_0 from ANOVA than from Snedecor distribution with small P-value at the same time). Two-factor interaction between workload and priority rule (UP) are also important issue in research model properties.

Table 1
Analysis of Variance for executed experiment.

Source of Variation	Sum of Squares	Degrees of freedom	Mean Square	F_0	P-value
B	1.63E+05	2	8.18E+04	0.1	0.882933
U	**8.36E+09**	**9**	**9.28E+08**	**1413.9**	**<0.00001**
P	**7.98E+06**	**5**	**1.59E+06**	**2.4**	**0.033361**
BU	1.72E+06	18	9.57E+04	0.1	0.999990
BP	4.96E+05	10	4.96E+04	0.1	0.999952
UP	**8.74E+07**	**45**	**1.94E+06**	**3.0**	**<0.00001**
BUP	1.45E+07	90	1.61E+05	0.2	1.000000
Error	7.09E+08	1080	6.57E+05		

We now discuss some typical results of the experimental analysis for the commercial offset printing.

The performances of the six rules under study are evaluated with respect to mean flow time of jobs, work-in-progress, equipment utilization, wait time at the most critical input buffer in front of offset machines and profit are presented in Figs. 2 and 3.

Figure 2 presents how profit is changing with change of priority strategy regardless of different levels of resource utilization. Vertical segments stand for 95% confidence intervals.

Figure 3 shows the profit function versus a priority rule with resource utilization as a parameter. It can be seen that for higher levels of utilization some priority rules are markedly better than others, for example for 99% utilization the best priority rule is SPT and the worst is LPT. On the other hand for 95% utilization level the best priority strategy is LPT. Looking horizontal at specific rule i.e. LOR one can see that this rule is sometimes the worst choice – 75% utilization, sometimes average – 65% utilization and sometimes the best choice – 90% utilization.

From the Fig. 4, which shows wait time for brochure product class versus priority rule at different levels of resource utilization, it can be seen that for the highest levels of resource utilization (when there are lot of jobs in the system) the best strategy minimizing book wait time is EDD and the worst are FIFO and LOR. Differences are big when utilization rate is high, for lower utilization rates differences are not as explicit.

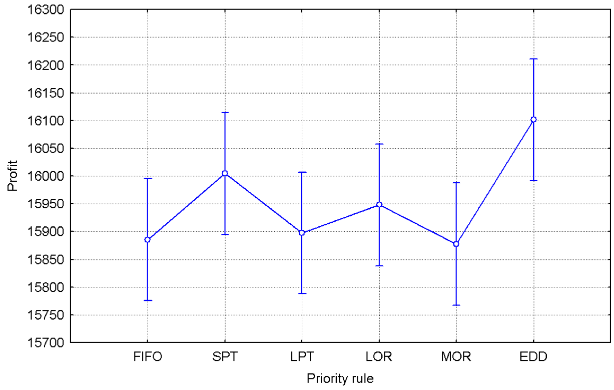

Fig. 2. Profit function versus priority rule.

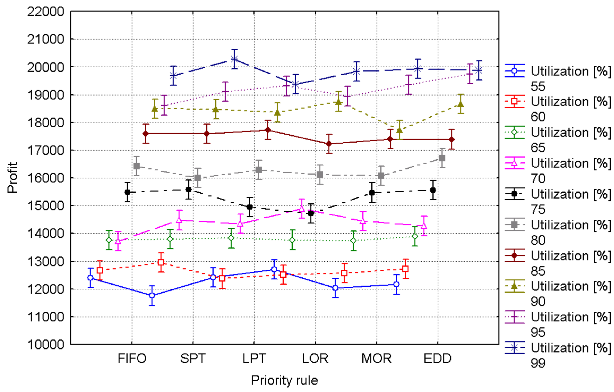

Fig. 3. Profit function versus priority rule.

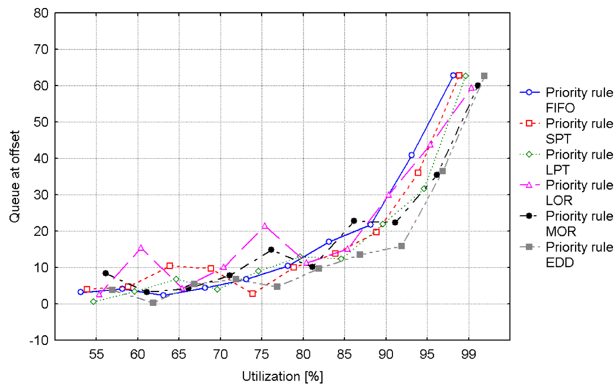

Fig. 4. Queue at offset versus resource utilization.

Figure 5 presents jobs number in queue for all types of products before offset station versus resource utilization for the different priority rules. The same increasing trend is seen for all priority strategies. For some levels of utilization there are rules with distinctive influence, i.e. for 60 and 75% level of utilization LOR strategy is especially unfavourable – queue is the highest. Some interesting characteristics of priority strategy influencing parameters of a model are shown in Fig. 6. One can observe the influence of the priority rule on the wait time for leaflet product class WIP (Work-In-Progress) for leaflet product class versus priority rule for different utilization levels. From the figure it can be seen that the worst rules (causing lot of jobs in the system) are SPT and MOR.

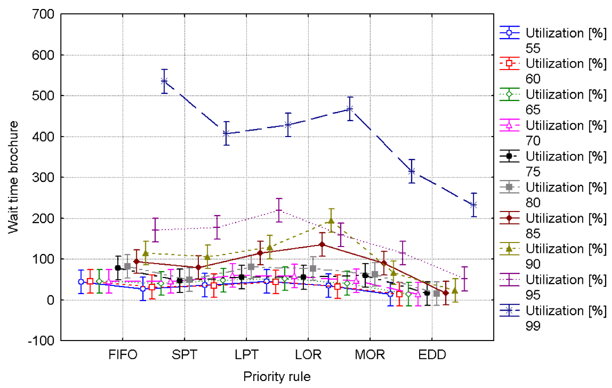

Fig. 5. Wait time for brochure product class versus priority rule.

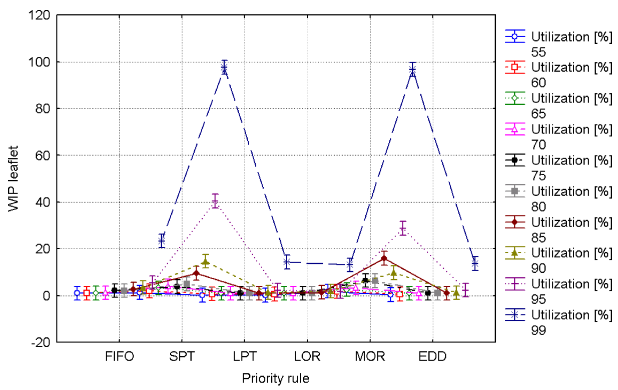

Fig. 6. WIP for leaflet product class versus priority rule.

At middle utilization levels analyzed commercial offset printing system is able to accomplish about 600 orders. Proper selection of priority rule provide up to 5% more executing orders and 7% profit increase. At the highest utilization level system is able to finish about 1000 orders in optimization period. Differences between the worst and the best priority rule reach 8% and when to consider profit only appropriate selection of the rule could lead to 10% profit increase.

Conclusions

Analysis of large and complex stochastic systems is a difficult task due to the complexities that arise when randomness is embedded within a system. Performance of various layout alternatives can be studied using simulation. In this paper there are presented reasons to use simulation in order to evaluate manufacturing system performance. There is also shown case study of commercial offset printing system to show how some management decision influent system performance. Commercial offset printing manufacturers are constantly under pressure to reduce cycle time, improve delivery performance, and decrease overall costs. In order to achieve these goals printer are either invest in equipment or try to reorganize workforce but they almost never recognize prioritization as an option. All figures show that priority strategy has an important impact on individual output parameters performance. For different output parameters there are different priorities rules which give better results. There is no best priority strategy for entire system. Basing on the obtained result it is possible to develop a decision rules that will advice a manufacturer which priority rule would be the best for a certain conditions and when to change it.

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