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TAUTOLOGIES, MODELS AND THEORIES:

CAN WE FIND "LAWS" OF MANUFACTURING?*

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ABSTRACT

Are there "laws" of manufacturing? If so, what do they look like? If not, what other forms of knowledge might comprise intellectual foundations for a discipline of manufacturing? We differentiate among mathematical tautologies, laws, models, and theories, giving examples of each. Laws closely analogous to those of nineteenth century physics appear to be unlikely but empirical models offer the prospect of building new understanding of manufacturing, even if they may lack the precision of their classical counterparts. Descriptive models serving scientific goals tend to differ from prescriptive models for problem-solving. The latter must be complete enough to solve the practical problem at hand and yet be selective in their detail so as not to paralyze problem-solving with irrelevant complication. A growing collection of parsimonious models and theories can form a basis for the design, analysis and control of complex manufacturing systems.

Manufacturing systems are man-made artifacts. Is it possible, in these created worlds, to discover what might be called "laws of manufacturing?" If so, it can be argued, such laws would help establish intellectual foundations for a discipline of manufacturing. On the other hand, if such laws cannot be found, what other forms of knowledge will help us design, analyze and control better manufacturing systems?

It may be useful to distinguish between several types of potential laws: (1) mathematical tautologies, (2) physical laws and their analogs, (3) empirical models and (4) theories. Then we can ask whether we are likely to develop further along each line. Moreover, we can look for related concepts that may be helpful in organizing our knowledge of manufacturing systems.

Tautologies vs Laws

$L=\lambda W$ ("Little's Law") is an example of a mathematical tautology with useful mappings onto the real world. $L=\lambda W$ relates the average number of items present in a queuing system to the average waiting time per item. Specifically, suppose we have a queuing system in steady state and let

L = the average number of items present in the system,

λ = the average arrival rate, items per unit time, and

W = the average time spent by an item in the system, then, under remarkably general conditions,

$$L = \lambda W. \qquad (1)$$

This formula turns out to be particularly useful because many methods for analyzing queuing systems produce either L or W but not both. Expression (1) permits an easy conversion between these two performance measures. Queues and waiting are ubiquitous in manufacturing: jobs to be done, inventory in-process, orders, machines down for repair, etc. Therefore, (1) finds many uses.

$L=\lambda W$ is a mathematical theorem, having no necessary relationship to the world. Given the appropriate set of mathematical assumptions, $L=\lambda W$ is true. There is no sense going out on the factory floor and collecting data to test it. If the real world application satisfies the assumptions, the result will hold.

The basic tautological nature of the proof can be illustrated by drawing a plot of the number of items in the system versus time as in Fig. 1. The area, A, under the curve represents the total waiting done by items passing through the system in the time period, T. Since the average number of items arriving in a time period, T, is λT, we have as the average wait per item (at least to first order, with an accuracy that increases as T becomes larger): $W = A/\lambda T$. However, the same area, if divided by the time, also represents the average number of items in the system during the period: $L = A/T$. Eliminating A from these two expressions gives (1).

Thus the two sides of equation (1) are really two views of the same thing and, with appropriate treatment of end effects and the taking of mathematical limits, become equal. (Notice that we have argued the existence of the relationship by considering a single sample of the queuing process. The generality of the formula and its independence from particular probability distributions arises because the argument holds for each specific evolution of the system.)

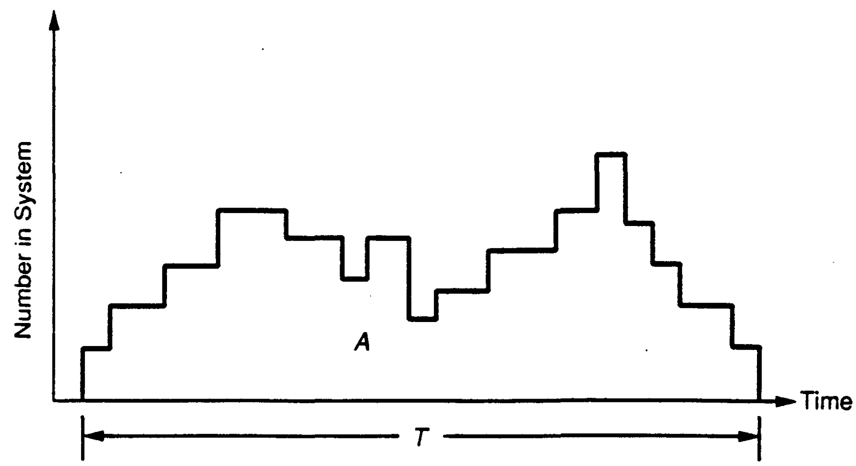

Fig. 1. The two sides of the queuing formula, L = λW, reflect two different views of the area A under the curve of number of items in the system vs. time. In the limit L tends to A/T and W to A/λT.

Physical laws are different. For example, the equality of the two sides of Newton's law, F=ma, cannot be taken for granted. Each must be measured separately and the equivalence verified experimentally. In fact, it is well known that F=ma is only approximate and breaks down at velocities approaching the speed of light. Thus physical laws require observation of the world and induction about the relationships among observable variables.

Laws vs Empirical Models

Nineteenth century physics produced many "laws of nature": Hooke's law, Ohm's law, Newton's laws, the laws of thermodynamics, etc. By the mid twentieth century, however, many of these laws had been found to be only approximate and many new, messy phenomena were being examined. As a result scientists became more cautious in their terminology and began speaking of models of phenomena. This continues to be the popular terminology today. Such is particularly true in the study of complex systems, social science phenomena, and the management of operations. The word, model, conveys a tentativeness and incompleteness that is often appropriate. We enter a class of descriptions of the world in which there are fewer simple formulas, fewer universal constants, and narrower ranges of application than were achieved in many of the classical "laws of nature."

Much valuable knowledge, however, can be packaged into empirical models of phenomena. Their accumulation into organized bodies of learning represents scientific advance and provides a basis for engineering and managerial practice. Here are a two examples.

If you examine communications between pairs of individuals in R&D groups vs. the physical distance between them, you find a curve like Fig. 2. (Allen, 1977). Although there is no strictly prescribed functional form or universal constant here, there is definitely a general shape and an experimentally determined range of parameter values. The regularity of the curves can be distorted by a variety of special circumstances, such as electronic mail, location of people

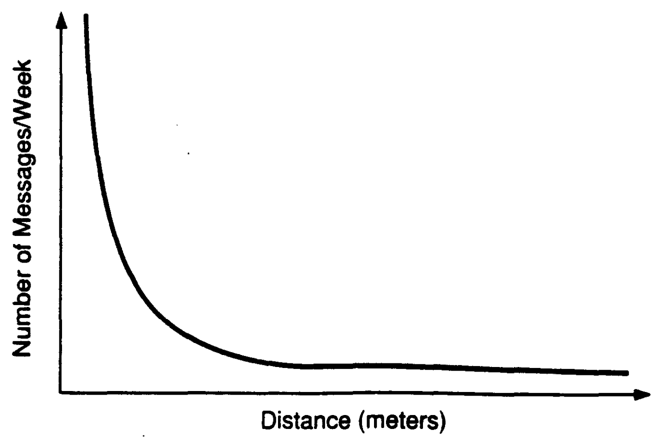

Fig. 2. The number of messages per week between pairs of people in an R&D group falls off rapidly with the distance between them. After Allen (1977).

on different floors, the presence of a coffee machine, etc., but the basic phenomenon is strong and its understanding is vital for designing buildings and organizing work teams effectively.

Another example is the experience curve, which is illustrated in Fig. 3. It is well known that manufacturing costs per unit tend to decrease with cumulative production. This has been documented in a variety of cases (see, for example, Hax and Majluf, 1984).
However, the experience curve is a somewhat different kind of a relationship from that of the communications example because the decreasing cost does not happen automatically. Rather it is the result of much purposeful activity in managing the manufacturing process. In a certain sense, this seems a little less satisfying, than, say, Newton's law, which predicts unequivocally the trajectory of a ball in free flight after it has been struck by a bat. But knowing about the experience curve, planning for it, and making it happen, form an important part of many firms'

strategies.

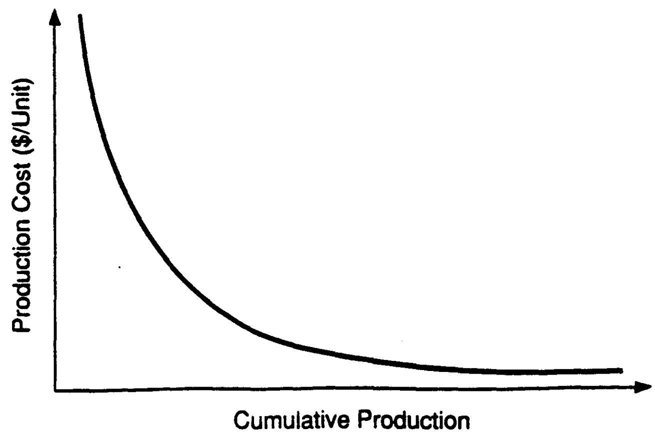

Fig. 3. The experience curve shows production cost/unit decreasing with cumulative units produced. After Hax and Majluf (1984).

Models vs. Theories

In the social sciences one often hears the term model when there is no equation, formula or other mathematical representation anywhere in sight. Coming from a background in physical science, I was perplexed when I first encountered this but finally realized that model in these contexts means theory in its everyday sense. Theory is a quite general term indicating a set of relationships among constructs. Some theories are mathematical, (for example, relativity theory), others, qualitative (as Darwin's theory of evolution).

A fine example of knowledge labeled as a theory comes from contemporary psychology.

Prospect theory (Tversky and Kahneman, 1981) describes how people make decisions under uncertainty. As a result of many experiments in which people make choices in different situations with uncertainties, Tversky and Kahneman have produced a descriptive theory of how people make such decisions. They illustrate it with Fig. 4.

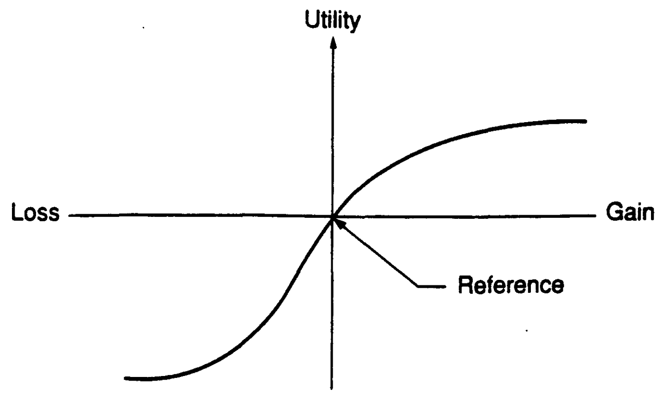

Fig. 4. Prospect theory describes an individual's utility as increasing in a concave function with gains and decreasing in a convex function with losses. After Tversky and Kahneman (1981).

Fig. 4 shows a hypothetical value function for an individual, expressing the person's utility for the outcome of some decision. The curve displays three interesting characteristics of people's behavior. First, people tend to make decisions based on potential gains or losses relative to some reference point. If you change the reference point you are likely to change how they value the possible outcomes of a choice and therefore may affect the choice itself.

For example, if a person has, as a reference point, a belief about the price of a particular product and then finds the item in a store at a lower price, he or she is likely to treat the difference as a potential gain. Subsequently, if the person buys the product, the purchase is likely to be considered especially satisfactory, and, in fact, the lower price may have helped stimulate the transaction. This is why stores that are running sales usually display the original price prominently. This sets a reference point and makes the discount a net gain for the customer.

A second characteristic of Fig. 4 is that the slopes for gains and losses are different near the origin. The steeper slope for losses indicates that most people dislike a loss more than they like a corresponding gain. This helps explain the current unfortunate tendency toward negative political advertising. A quantity of negative information suggesting that a candidate might do something harmful if elected may have more influence on the voters than a similar quantity of positive information.

As a third property, Fig. 4 indicates that people treat gains and losses differently by showing a concave curve for gains and a convex one for losses. The concavity for gains says, for example, that two separate small rewards to an employee are likely to be appreciated more than a single reward with the same total value. The convexity of losses means that people find it mentally desirable to combine a number of small losses into a large one, as we do when we charge by credit card and pay a monthly total bill instead of several individual ones.

Prospect theory is even further away from the well-calibrated formulas of nineteenth century physics than the empirical models described previously. Notice that Fig. 4 has no units on its axes and even the terms utility, gain and loss seem to be a little vague. Such apparent sloppiness would be quite disconcerting in engineering or physical science. Yet the shape of the curve serves to summarize a great many experiments and sheds light on a whole variety of phenomena. Contemporary psychology is making impressive strides in understanding human behavior, but it often does so more by identifying phenomena and indicating the direction of effects than by producing calibrated models analogous to physical laws.

Models for Science vs. Models for Problem-Solving

The models, theories, and mathematical relations discussed above are candidates to be part of the intellectual foundations of a discipline of manufacturing. They are descriptive of phenomena in a traditional scientific way. But models play other important roles as well.

Models for problem-solving often differ from models for science. The difference lies in the criteria, both for choosing what to model in the first place and for judging the model when it is finished. In addition, the process of building the model changes.

Science is concerned with describing the universe with fidelity and parsimony. These fundamental criteria tend to identify which work survives to be recapitulated in the text books of the next generation, although scientists care about other attributes as well - they talk about elegance, beauty, surprise and delight. Scientists have developed a variety of tests for assessing fidelity, for example, the notion of trying to falsify a result. This often involves developing alternative hypotheses and devising critical experiments or observations that will discriminate among them. There are also predictive tests. And one can try to think up threats to validity and evaluate their seriousness.

Models for problem-solving have different goals. Most of us in engineering or management science are trying to help organizations make improvements in the world, or at least our corner of it. This is certainly true in manufacturing. Having such a goal tends to change and clarify the model-building process. It is also likely to lead to complicated rather than parsimonious models because the systems we wish to understand and control are complex. Complicated models provide us with knowledge but would not be called laws.

A key difference in the problem-solving case is that we presuppose a client or customer. This might be a manager, an organization, or possibly society as a whole. The model-builder may be thought of as a consultant, often an internal one, and model-building is imbedded in a larger organizational process. We now find different criteria from those used in scientific model-building. The principal purpose is to improve the client's welfare, not just describe the system.

Interestingly, I can think of many more how-to-do-it lists for the problem-solving side of model-building than for purely scientific work. People have devised a variety of paradigms to help the model-builder. Examples are: (1) systems analysis (Miser and Quade 1985), (2) the phases of OR (Churchman, Ackoff, and Arnoff, 1957) and (3), Urban's (1974) "Building Models for Decision Makers." The last is particularly interesting because it explicitly considers the consulting process itself.

Recipes like these are frequently useful. They are check lists that help jog people's thinking into directions that need to be examined, although such paradigms mean most to people who have already tried to build models for problem-solving. To others, the prescriptions seem vague. I find, for example, that undergraduate students often see these paradigms initially as empty talk, but after a summer job trying to solve practical problems, they relate to the ideas quite easily. A really experienced person is also likely to find them superficial because the main points have long since been internalized and second order subtleties have become salient.

Models for problem-solving have a surprising requirement that is quite different from models for science. Problem-solving models should be incomplete. They should include that which is important to the task at hand and leave out that which is not (Little, 1970). For decision-making purposes we want to restrict ourselves to the detail needed for the job (but should be complete in this). Such a requirement for artful imperfection is familiar to all practicing engineers and management scientists but to almost none of their clients, a situation that can cause confusion and miscommunication.

The exhortation to be complete on important issues and leave out unimportant ones begs the question of how to determine which is which. Anybody who has done analyses in live contexts, however, knows well the pressure from the client and the critics to include more and more detail in the model, and the importance of resisting many of these pressures. This is necessary to prevent a modeling project from becoming too large and unwieldy and to avoid a downhill slide toward expending more and more resources on activities that are not going to affect the results. There are tough calls that require side analyses and off-line arguments to make the necessary design decisions. One of the difficulties in keeping models from becoming overly complicated is that there are always aspects of the problem that are unimportant but can be blown out of proportion by word pictures and one-of-a-kind anecdotes. Ironically, clients often reject models because of a lack of some feature and then go on to make decisions on the basis of far simpler mental models and heuristics.

We conclude that most models for problem-solving are not candidates to be fundamental laws but are artful constructions which provide the practical payoffs that justify building a discipline in the first place.

Simple vs. Complex Models

Ideally, potential laws of manufacturing would be simple in statement and general in applicability. Yet manufacturing systems are usually complex and specific, involving not only machines and organizations of people, but many and varied information flows and control processes. How is this situation to be handled?

Since, as humans, we have finite intellectual capacity or "bounded rationality" (Simon,1957), we tend to break complex systems down into small, manageable pieces for analysis, design and control. Once we have decomposed a system into parts, we then have a desire to resynthesize small entities into big ones and work with the large entities as new units. Such hierarchical modeling is a useful approach, but not without pitfalls. Forrester (1961) points out that the parts of the system sometimes interact in unexpected ways and offers system dynamics as an approach for treating this.

Large scale simulations performed in computer languages designed for the purpose are now quite common (Pritsker, 1990, Cooper, 1990). We have outstanding computer capabilities and increasing experience in modeling complex systems. However, care must always be exercised in order not to lose the main points amid the detail. I would argue for having simple models both before and after a large scale simulation. Before one begins, it is important to ask what phenomena are critical to the decision at hand. It can be helpful to build a few-variable back-of-the-envelop model to represent these phenomena. It is likely that such a model will make too many simplifying assumptions to be accepted by the client. and so a more detailed model may be necessary. However, if the results of running a complex model suggest a particular course of action, it is imperative to know why the model produced those results, i.e., what were the key assumptions and parameter values that made things come out as they did. In essence, we should have a simple model with a few key variables that boils down the essence of why the recommendations make sense.

The building of more and more complicated models of systems using the same methodologies runs into diminishing returns. Managers face dozens of different problems each day: not just late schedules, low throughput and excess inventories but also issues such as key people being hired away, roofs that leak, complaining customers, absentee employees, etc. Thus there is a need for multiple views; a hundred different small models are often desired, not a single big one.

Modeling myopia

People trained in engineering or management science tend to think top-down, that is, in terms of goals, objective functions, design variables, models of processes, synthesis of systems from subsystems and the like, with the intent of using the entities under their control to maximize system performance. Consider, however, the following quote from a talk by Mr. Konosuke Matsushita of Matsushita Electric Industrial Company (Stevens, 1989).

> "We are going to win and the industrial west is going to lose; there's nothing much you can do about it because the reasons for your failure are within yourselves. Your firms are built on the Taylor model; even worse, so are your heads. With your bosses doing the thinking while the workers wield the screwdrivers, you're convinced deep down that this is the right way to run a

business. For you, the essence of management is getting the ideas out of the heads of the bosses and into the hands of labor. We are beyond the Taylor model; business, we know, is now so complex and difficult, the survival of firms so hazardous in an environment increasingly competitive and fraught with danger, that their continued existence depends on the day-to-day mobilization of every ounce of intelligence."

Whether or not Mr. Matsushita's forecast is correct, he forcefully articulates a critical idea - the need for empowering and enhancing the effectiveness of people at all levels of an organization.

We indulge in modeling myopia if, as system analysts, we believe we can (or should) be building complete models of our systems and setting all the control variables. Doing so misses major opportunities for system improvement that are possible by finding new ways to empower the people on the front lines of the organization by giving them information, training, and tools with which to improve their own performance.

Also implicit here is the recognition that organizational coordination is something much more than top-down control. New ideas are evolving in this area, for example, developments in computer assisted collaborative work and coordination theory (Malone and Crowston, 1991). As information technology has decreased the cost of communication, there has been a growth of lateral communication and coordination and a shift from vertically hierarchical organizations to more lateral and market-like structures. Lateral coordination is valuable in speeding new product development, finding process improvements, implementing new ideas and generally facilitating parallel but interdependent operations in different locations.

But what kind of knowledge is this? And how is it tested and proved valid or not? Certainly there are testable propositions and empirical models and theories to be created here and they hold opportunities for building more effective manufacturing systems.

Outlook for laws of manufacturing

What can we anticipate, then, in terms of laws of manufacturing? Are there more laws like $L=\lambda W$? Probably so, in the sense that we should be able to find other simple but fairly general mathematical rules and relationships that map well onto the world and provide valuable insights about operations. An example might be the "shortest job first" priority that minimizes average wait in system across a rather broad class of queuing systems.

I am less optimistic about finding many analogs of physical laws because our systems are quite complicated and messy. Of course, we use the laws of physics directly in the engineering of manufacturing systems. And we readily write down material flow equations equating inputs and outputs in an intuitive application of conservation of matter. But our complex manufacturing systems do not seem to invite new laws like $F=ma$. In part this may be because manufacturing systems are built of subunits that we, as designers, have defined, both in terms of the atomic entities and the rules of connecting them. We therefore know the underlying relationships already and take them for granted. This is different from the physical world, which was given to us as an undeciphered puzzle, and where the game has been to figure out how things work inside the black box.

Manufacturing systems are characterized by large, interactive complexes of people and equipment in specific spatial and organizational structures. Because we often know the subunits already, the special challenge and opportunity is to understand interactions and system effects. There are certainly patterns and regularities here. It seems likely that researchers will find useful empirical models of many phenomena in these systems. Such models may not often have the cleanliness and precision of Newton's laws, but they can generate important knowledge for designers and managers to use in problem solving.

As we analyze manufacturing systems, building models of them to understand their behavior and help with their design and operations, we shall be building complex, problem-solving models, more often than descriptive, scientific models, although we shall use all of the latter we can in the process. Ideally, however, our analyses will find summary regularities that might be called principles or theories and hold over reasonably wide ranges of conditions. These may be in the form of rules of thumb or few-variable models that capture the essence of some phenomenon. These will represent the creation of new fundamental knowledge.

Such work is in fact accumulating. An example might be the work of Wein and Chevalier (1992). In studying job-shop scheduling (assigning due dates, releasing jobs from backlog, and sequencing jobs at workstations), these researchers report simplifying principles of scheduling that decrease the amount of work in progress and improve due-date performance. Their heuristics are motivated by exact solutions of special cases but can be shown by simulation to be effective in a range of complex systems. Furthermore, the reasons why the principles work well (which, in this case, are related to system bottlenecks) can be described and understood qualitatively.

Finally, in analyzing, designing and managing manufacturing systems we need to bring in organizational and managerial knowledge, integrating this with operational and engineering content built up from a few laws, many good empirical models and a variety of theories, but avoiding model myopia. Many issues will arise that offer fruitful research agendas.

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