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# A survey of inspection strategy and sensor distribution studies in discrete-part manufacturing processes

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Methodologies, modeling approaches, and the interactions between various system elements involved in inspection-allocation and sensor-distribution problems, that influence operational quality decisions, are discussed. The surveyed papers fall into two broad categories: inspection-oriented quality-assurance strategies and diagnosis-oriented sensor-distribution strategies. Within each subarea, individual papers are further classified according to the system characteristics of the physical processes being investigated and the modeling characteristics of the approaches being used. As evident from nearly 100 journal articles published in the past four decades, these two problems have received considerable attention from researchers in quality engineering, management science, operations research as well as robotic vision arenas. We find that the inspection-allocation problem has been studied rather comprehensively whereas the relatively new sensor-distribution problem has plenty of opportunities for researchers. Discussions are also presented to summarize our observations based on the classifications along with some thoughts on future research.

## 1. Introduction

Producing high-quality products is a crucial factor in an enterprise maintaining its global competitiveness. Operations managers tend to view quality as being the fraction of products that are made right the first time in each of the various stages that constitute a manufacturing process. More quantitatively, quality is defined to be inversely proportional to variability, and quality improvement is then equivalent to variation reduction (Montgomery, 2003).

Since almost all manufacturing processes are technologically incapable of delivering perfect quality, establishing an effective quality-assurance program by planning and managing resources dedicated to the inspection and testing of critical product attributes is important. Human inspectors, automated sensing devices (e.g., an image analyzer in a machine vision system), or a combination of both are often used for quality-assurance purposes. The inspection or measurement-taking may simply be process checks for defects resulting from an individual process that has just been completed, or may be a part of a more comprehensive diagnosis that traces an underlying anomaly that has existed for a number of previous processes.

Introducing inspection stations or deploying sensing devices in a production process, although constituting an additional cost, is expected to be a profitable course of action since at some point the associated costs will be recovered from the benefits realized via the detection of defective items and isolation of defect-causing variation sources. If one only inspects, reworks, or scraps a finished product, the inspection cost is low. However, scrapping a finished product is usually expensive; its influence on the final product quality is direct but its contribution to the variation-source diagnosis is often limited. If, however, one adopts a strategy of inspecting, reworking, or scrapping upstream intermediate products then the inspection costs could increase considerably but the scrapping of an unfinished product may be relatively inexpensive. Also, whereas its influence on the overall final product quality is indirect, its ability to facilitate variation-source diagnosis is often good. Any sound inspection strategy will have to consider the needs of multiple stakeholders and make reasonable trade-offs between their objectives.

Therefore, when and where in a production process an inspection should be performed or sensing devices be distributed is an important and challenging decision in quality control. The various cost and constraint factors as well as operational alternatives interact in an intricate fashion and make the solution far from trivial. Research efforts have been made to address this objective over the past four decades and they are still going on today. The intention of this paper is to survey the relevant literature and to present a summary of the research in this area.

We find that the relevant research efforts can be generally classified into two broad categories: (i) inspection-oriented quality-assurance strategies; and (ii) diagnosis-oriented sensor-distribution strategies. An inspection-oriented quality-assurance strategy attempts to allocate an economically appropriate level of inspection activity by striking a balance among the various cost components associated with inspection, repair and replacement due to quality failure, and/or the warranty penalty in the case where a nonconforming product has been shipped to customers. In other words, an inspection-oriented strategy focuses on an optimization that minimizes the total manufacturing costs associated with quality appraisal and failure.

Although an inspection-oriented strategy potentially improves the quality of products eventually going to customers, it does nothing to alter the *overall product quality*, since nothing has been done to improve the underlying process. Ideally to ensure satisfactory product quality, the role of measurement-taking should be to diagnose the underlying sources that caused the defect and provide immediate feedback to workers and suppliers so that they can make adjustments to the process as soon as any defects occur. In such an endeavor, people usually assume that a set of underlying yet unknown variables are responsible for the quality defects. These underlying variables are usually not directly observable, and hence, inferences about their status have to be made based on sensor data in order to determine which variable(s) are causing the quality problem. Instead of simply minimizing the overall cost, a diagnosis-oriented strategy imposes either diagnosability or estimation accuracy requirements as a constraint, while finding the optimal way to deploy sensors. The diagnosis-oriented strategy is also known as the sensor-distribution strategy.

The difference between the two approaches is caused by differences in their respective assumptions about the behavior patterns of manufacturing costs. An inspection-oriented strategy emphasizes a cost-effective production and tolerates a nonzero level of defective production. A diagnosis-oriented strategy focuses on the creation of a near-zero level of defective production. It is interesting to note that the two types of research have been conducted rather independently without much overlap between them.

A few surveys have been previously performed including those of Dorris and Foote (1978), Menipaz (1978) and Raz (1986) all of whom covered research topics related to the inspection-oriented quality-assurance strategy. Research into diagnosis-oriented strategies is relatively recent and to the best of our knowledge no survey on this area has been previously reported.

It has been almost two decades since the survey of Raz (1986). In the intervening period, sensor technology has significantly advanced and its application to quality inspection has greatly expanded. Considerable effort has been expended on the investigation of new research issues, the improvement of existing models or methods, and the exploration of untested application domains. The present survey will cover those papers published since Raz (1986) on the topics of inspection and sensor-distribution strategies, and it will also provide more details regarding the system and model characteristics.

In this survey, our focus is confined to research with direct applications to *discrete-part manufacturing* processes. Thus, studies on sensor placement methods in continuous-flow processes or dynamic systems (Kubrusly and Malebranche, 1985) as well as the application of sensor networks to surveillance and target localization (Chakravarty *et al.*, 2002) are not included in this survey, although they bear certain similarities to the work surveyed here, particularly to diagnosis-oriented strategies.

This survey primarily focuses on journal articles since refereed journals are arguably the major outlet for original technical publications and thus they are expected to reasonably reflect the trends in technology developments. For this reason, we have studied articles in those journals in which the surveyed topic was likely to be published, including *Management Science*, *International Journal of Production Research*, *European Journal of Operations Research*, *Operations Research*, *Journal of Quality Technology*, *Technometrics*, *Journal of the American Statistical Association*, *ASME Transactions*, *IEEE Transactions*, *IIE Transactions, Transactions of NAMRI/SME, Journal of Manufacturing Systems, International Journal of Flexible Manufacturing Systems*, *Annals of the CIRP*, and *Computers & Industrial Engineering* among others. We believe that the survey is reasonably comprehensive.

We hope that this survey can serve two sets of readers. The first set is comprised of readers who are familiar with the inspection strategy or sensor-distribution research and are looking for some simplifying insights, unifying principles, and/or the trends in the research activity. The second set is comprised of readers who are new to this research area and are looking for an overview of the field before begining to work in this area.

Following this Introduction, the paper is organized as follows. Section 2 will cover publications related to inspection-oriented quality-assurance strategies. Section 3 will cover publications related to diagnosis-oriented sensor-distribution strategies. A general discussion and some perspectives on future research directions are presented in Section 4.

## 2. Inspection-oriented quality-assurance strategies

### 2.1. *Problem background*

The problems associated with formulating an inspection strategy have been explained in numerous individual research papers as well as in the survey paper by Raz (1986). In order to make this survey a self-contained entity and also to provide a basis for later discussions, we will briefly go through the decision-making process involved in the inspection of a finished product or a semi-finished product.

As illustrated in Fig. 1, the question of whether or not to inspect a final or semi-finished product can be asked after every manufacturing operation. If the answer is *yes*, then

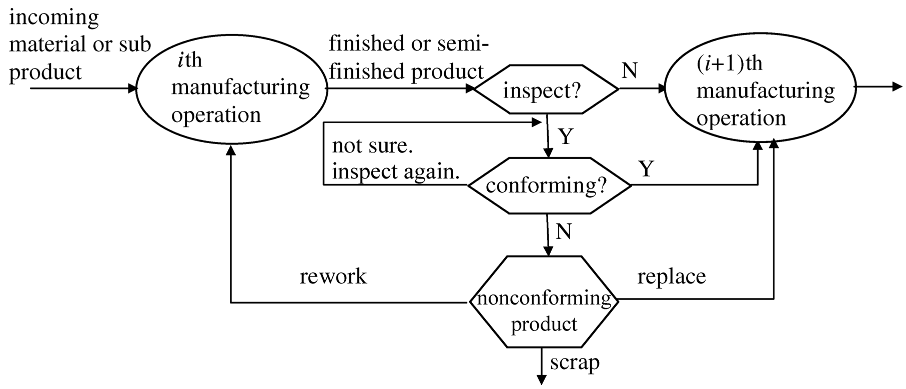


**Fig. 1.** The inspection allocation problem in manufacturing quality control.

one will need to decide on an inspection threshold or a specification region for conforming items. In cases where the inspection is performed on a batch of items instead of a single item, one also needs to determine if all or a fraction of the items should be inspected. After inspection, the item(s) may be deemed as being either conforming, or nonconforming, or indeterminate. Conforming items will then go on to the next operation. There are several possible outcomes for nonconforming items: (i) they may be replaced with a conforming item which is then sent for the next processing operation; (ii) they may be sent back for rework/repair; or (iii) they may be simply scrapped. Indeterminate cases are usually due to poor measurement statistics and this problem is simply alleviated by performing repeated inspections.

It should be noted that not all the questions raised above are answered in every case studied in the literature. There are cases in which the locations where an inspection can be made are fixed (e.g., at the end of a production line) before the production process is built. These inspection strategies will therefore answer questions such as the fraction of items to be inspected, the number of repetitions, and how to deal with a nonconforming item. We refer to this type of work as a *parametric strategy*, whereas research involving the determination of where to allocate inspection capability is referred to as an *allocation strategy*.

It is also worth noting that the literature on inspection strategies does not differentiate between inspections conducted by automated devices, human inspectors, or a mix of both (e.g., human inspection following an automatic inspection). This is because the actual inspection actions are usually modeled using a set of parameters that are independent of the actual inspection methods (such as type-I and type-II errors and the number of repetitions).

Finally, we would like to point out that the following assumptions are commonly made in the work surveyed here:

1. both the product and the process are discrete;
2. product quality is dichotomous;
3. customers perfectly determine the product quality.

In the subsequent sections, we present a classification of publications using various criteria. In Section 2.2, we first discuss the characterization of a physical manufacturing system, inspection capability, and the behavior pattern of quality defects. In Section 2.3, we discuss the optimization modeling for the inspection strategy and the associated solution methods. In Section 2.4, we look into the publication trend over the past decades.

## 2.2. *System characteristics*

Based on the systems studied in the existing literature, the following six major aspects appear to be used to characterize a manufacturing process: (i) production configuration; (ii) item flow; (iii) inspection type; (iv) inspection capability; (v) defect rate; and (vi) defect reparability.

### 2.2.1. *Production configuration*

There are three major process configurations based on the flow of conforming items: (i) serial/sequential systems; (ii) assembly/convergent systems; and (iii) nonserial systems (please see Fig. 2). In a serial production system, the input material passes through successive processing workstations sequentially, whereas in a nonserial system the input material takes one of several paths through a production system, i.e., certain stations may be involved in joining the outputs of multiple previous stations. One special case of the serial systems is a single-station/stage manufacturing process. One special nonserial system is the assembly/convergent system (Garcia-Diaz *et al.*, 1984; Gunter and Swanson, 1985; Zheng, 2000), shown in Fig. 2(b), where each workstation has at most one successor but many predecessor workstations (Fig. 2(b), however, shows only the case with two predecessor workstations). This special nonserial system has received significant attention perhaps because it is a simple nonserial form that is relatively easy to solve mathematically. A system that is neither serial nor assembly falls into the general category of nonserial systems, of which Fig. 2(c) is just one simple example.

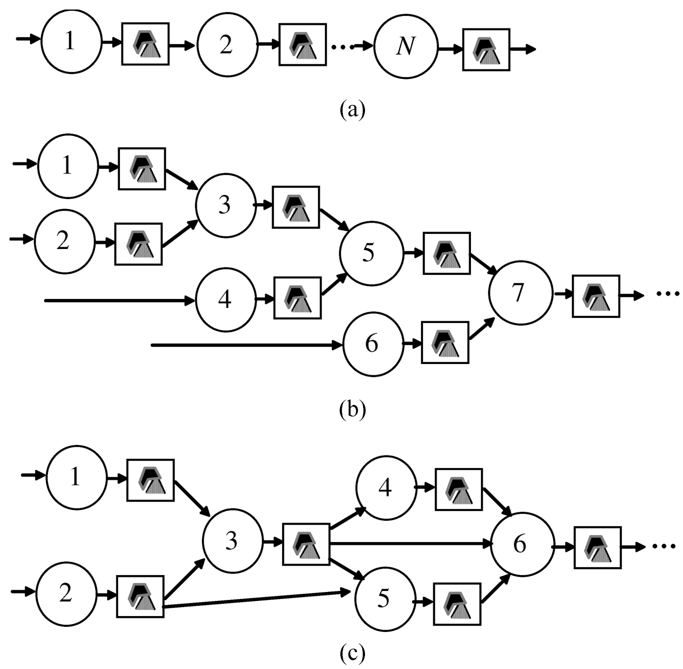


**Fig. 2.** Process configurations: (a) a serial/sequential system; (b) an assembly/convergent system; and (c) a nonserial system.

2.2.2. *Item flow*

A production line can manufacture either a single type of product or it can be used for multiple types of products from the same product family. During production, the items can flow through an inspection station either as a single item or as part of a batch (or a lot). There are a total of four possibilities: (i) the same product in a single item; (ii) the same product in a batch; (iii) mixed products in a single item; and (iv) mixed products in a batch.

2.2.3. *Inspection type*

If an inspection is performed, it may choose one of four actions: (i) a simple inspection is to inspect a single item once; (ii) a fractional inspection is to inspect a fixed fraction of items in a batch, where zero and one (full batch) are the two extreme cases; (iii) a repeated inspection is to inspect the same item(s) more than once; and (iv) a dynamic inspection is to inspect items in a batch sequentially and a decision of whether to reject or accept the batch is made dynamically instead of at a fixed fraction. One may confuse a repeated inspection with a dynamic inspection because both will have to take at least another inspection before reaching a decision. The difference is that for the next inspection, the repeated inspection is to inspect the same item or the same batch of items, whereas the dynamic inspection is to inspect a different item (in dynamic inspection, each individual item is usually inspected only once).

2.2.4. *Inspection capability*

Two types of errors are associated with an inspection: (i) the wrong rejection of a conforming unit which is known as type-I error; and (ii) the erroneous acceptance of a nonconforming unit which is known as type-II error. Not all the authors have considered both types of errors. Some have only considered one of the two types and some other authors have simply assumed a perfect inspection (i.e., error free).

2.2.5. *Defect rate*

Defect rate is the proportion of defective items among all items manufactured by a process at a stage. Together with the next aspect, they provide a characterization of the behavior pattern of quality defects. Some authors have assumed a known *constant* defect rate for all operations, whereas others have either assumed a possible range of defect rates (usually from zero to an upper bound) and assigned an occurrence probability for each defect rate or explicitly treated the defect rate as a random variable following certain distribution: both of which are labeled as a *random rate* approach. Researchers have also considered a single defect type, assigned with one variable for the defect rate, as well as multiple defect types, assigned with a vector of defect rates associated with each type of defect. Thus, we have four potential combinations: (i) single type constant; (ii) single type random; (iii) multiple type constant; and (iv) multiple type random.

2.2.6. *Defect reparability*

Once a defective item is detected during inspection, certain actions will be taken to repair, replace, or simply scrap it. What action follows the defect detection will depend not only on the cost associated with that subsequent action but also on knowledge of whether the defect is reparable since certain types of defects cannot be repaired. Hence, researchers have assigned a reparability level for defects. A deterministic assignment of reparability means that for a given type of defect whether or not it is reparable is predetermined. However, this may involve three different situations in which all, none, or some of the defects are reparable. Some authors have adopted a probabilistic approach which assumes that a defect is reparable with a given probability. Namely, all repairs may not be perfect and all the repaired items may be subject to a probability of incurring a defect on subsequent processing as they did in the original processing. When the action of *replacin*g the defective item is taken, it is equivalent to either the case in which all the defects are reparable if the *replaced* item is assumed defect free or the case in which the defects are reparable with a probability if the *replaced* item is assumed to be subject to a defect with a probability.

As such, we classify the existing literature into different categories associated with each of the aspects. Table 1 presents a summary of the classifications, where each publication is represented by only the first author's name followed by a two-digit publication year in order to save space. To know what type of manufacturing and inspection system a publication considered, one needs to pool

**Table 1.** Classification of the literature according to system characterization

| *System characterization* | *Classification* | *Publications* |
|---|---|---|
| 1. Production configuration | Serial/sequential | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Ercan ('72), Garey ('72), Woo ('72), Hurst ('73), Dietrich ('74), Eppen ('74), Ercan ('74), Trippi ('74), Enrick ('75), Trippi ('75), Ballou ('82), Hsu ('84), Peters ('84), Ballou ('85), Chakravarty ('87), Lee ('87), Peters ('87), Yum ('87) Tayi ('88), Barad ('90), Foster ('90), Kang ('90), Raz ('91), Tang ('91), Villalobos ('91), Villalobos ('93), Jewkes ('95), Rebello ('95), Shin ('95), Deliman ('96), Gurnani ('96), Viswandham ('96), Chevalier ('97), Chen ('98), Lee ('98), Yao ('99a), Yao ('99b), Veatch ('00), Shiau ('02), Shiau ('03a), Shiau ('03b), Kakade ('04), Valenzuela ('04) |
| | Assembly/convergent | Garcia-Diaz ('84), Gunter ('85), Viswandham ('96), Zheng ('00) |
| | Non-serial | Britney ('72), Yum ('81), Narahari ('96), Rabinowitz ('97), Chen ('99), Emmons ('02) |
| 2. Item flow | Same type in a single item | Britney ('72), Garey ('72), Garcia-Diaz ('84), Gunter ('85), Lee ('87), Foster ('90), Raz ('91), Tang ('91), Villalobos ('91), Villalobos ('93), Jewkes ('95), Rebello ('95), Shin ('95), Deliman ('96), Narahari ('96), Chevalier ('97), Rabinowitz ('97), Veatch ('00), Kakade ('04), Valenzuela ('04) |
| | Same type in a batch | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Ercan ('72), Woo ('72), Hurst ('73), Dietrich ('74), Eppen ('74), Ercan ('74), Trippi ('74), Enrick ('75), Trippi ('75), Yum ('81), Ballou ('82), Hsu ('84), Peters ('84), Ballou ('85), Peters ('87), Yum ('87), Tayi ('88), Barad ('90), Kang ('90), Gurnani ('96), Viswandham ('96), Chen ('98), Yao ('99a), Yao ('99b), Veatch ('00), Zheng ('00), Shiau ('02), Shiau ('03a), Shiau ('03b) |
| | Mix type in a single item | Chen ('99), Emmons ('02) |
| | Mix type in a batch | Chakravarty ('87), Lee ('98) |
| 3. Inspection type | Simple | Britney ('72), Garey ('72), Gunter ('85), Lee ('87), Foster ('90), Tang ('91), Villalobos ('91), Villalobos ('93), Jewkes ('95), Rebello ('95), Shin ('95), Deliman ('96), Narahari ('96), Chevalier ('97), Rabinowitz ('97), Veatch ('00), Kakade ('04), Valenzuela ('04) |
| | Fraction | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Ercan ('72), Hurst ('73), Eppen ('74), Ercan ('74), Trippi ('74), Enrick ('75), Trippi ('75), Ballou ('82), Hsu ('84), Peters ('84), Ballou ('85), Chakravarty ('87), Peters ('87), Yum ('87), Tayi ('88), Barad ('90), Gurnani ('96), Lee ('98), Veatch ('00), Shiau ('02), Shiau ('03a), Shiau ('03b) |
| | Repeated | Yum ('81), Garcia-Diaz ('84), Kang ('90), Raz ('91), Deliman ('96), Viswandham ('96) |
| | Dynamic | Woo ('72), Dietrich ('74), Rabinowitz ('97), Chen ('98), Yao ('99a), Yao ('99b), Zheng ('00) |
| 4. Inspection capability | Error free/perfect | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Britney ('72), Ercan ('72), Garey ('72), Woo ('72), Dietrich ('74), Ercan ('74), Trippi ('74), Trippi ('75), Hsu ('84), Peters ('84), Gunter ('85), Chakravarty ('87), Tayi ('88), Tang ('91), Jewkes ('95), Gurnani ('96), Narahari ('96), Rabinowitz ('97), Chen ('98), Chen ('99), Yao ('99a), Yao ('99b), Zheng ('00), Emmons ('02), Kakade ('04), Valenzuela ('04) |
| | Type-I error | Lee ('87), Peters ('87) |
| | Type-II error | Garcia-Diaz ('84), Rebello ('95), Shin ('95), Deliman ('96), Veatch ('00) |
| | Both error types | Hurst ('73), Eppen ('74), Enrick ('75), Yum ('81), Ballou ('82), Ballou ('85), Yum ('87), Barad ('90), Foster ('90), Kang ('90), Raz ('91), Villalobos ('91), Villalobos ('93), Viswandham ('96), Chevalier ('97), Lee ('98), Shiau ('02), Shiau ('03a), Shiau ('03b) |
| 5. Defective type in the system and defect rate at the stage | Single type constant | Lindsay ('64), White ('65), Brown ('68), Ercan ('72), Garey ('72), Hurst ('73), Eppen ('74), Ercan ('74), Enrick ('75), Yum ('81), Ballou ('82), Garcia-Diaz ('84), Hsu ('84), Peters ('84), Ballou ('85), Gunter ('85), Yum ('87), Tayi ('88), Foster ('90), Kang ('90), Raz ('91), Tang ('91), Villalobos ('91), Villalobos ('93), Jewkes ('95), Shin ('95), Deliman ('96), Gurnani ('96), Narahari ('96), Viswandham ('96), Rabinowitz ('97), Emmons ('02) |

*(Continued on next page)*

**Table 1.** Classification of the literature according to system characterization *(Continued)*

| *System characterization* | *Classification* | *Publications* |
|---|---|---|
| | Single type random | Beightler ('64), Dietrich ('74), Chen ('98), Yao ('99a), Veatch ('00), Shiau ('02), Shiau ('03a), Shiau ('03b) |
| | Multiple type constant | Pruzan ('67), White ('69), Britney ('72), Woo ('72), Trippi ('74), Trippi ('75), Chakravarty ('87), Lee ('87), Peters ('87), Barad ('90), Rebello ('95), Lee ('98), Chen ('99), Kakade ('04), Valenzuela ('04) |
| | Multiple type random | Chevalier ('97), Yao ('99b), Zheng ('00) |
| 6. Defect reparability | All (deterministic) | Beightler ('64), White ('65), Brown ('68), Ercan ('72), Ercan ('74), Trippi ('75), Yum ('81), Garcia-Diaz ('84), Hsu ('84), Lee ('87), Tayi ('88), Jewkes ('95), Shin ('95), Gurnani ('96), Chevalier ('97), Chen ('98), Yao ('99a), Yao ('99b), Veatch ('00), Zheng ('00) |
| | Some (deterministic) | White ('69), Britney ('72), Trippi ('74), Enrick ('75), Peters ('84), Yum ('87), Kang ('90), Rebello ('95), Lee ('98), Chen ('99), Shiau ('02), Shiau ('03a), Shiau ('03b), Kakade ('04), Valenzuela ('04) |
| | None (deterministic) | Lindsay ('64), Pruzan ('67), Garey ('72), Woo ('72), Hurst ('73), Dietrich ('74), Eppen ('74), Ballou ('82), Ballou ('85), Gunter ('85), Peters ('87), Foster ('90), Tang ('91), Villalobos ('91), Villalobos ('93), Viswandham ('96), Rabinowitz ('97), Emmons ('02) |
| | Probabilistic | Chakravarty ('87), Raz ('91), Narahari ('96), Deliman ('96), Barad ('90), Veatch ('00) |

the information under different categories. For example, Lindsay and Bishop (1964) considered a serial system with the same type of product inspected in a batch. The inspection is assumed to be error free and a fixed fraction is used without repetition. In their paper, a single defect type is assumed with a constant defect rate across the production stage and defective units are scrapped. Some of the publications appear in multiple categories because they consider multiple scenarios in a production system. For example, Veatch (2000) considers both a single item flow and a batch flow with corresponding inspection methods. Also, the paper considered the perfect repair case for product defects as well as the probabilistic imperfect repair case.

## 2.3. *Modeling characteristics*

An inspection-oriented quality-assurance strategy is generally solved through an optimization formulation. The objective is to minimize the costs that result due to the inspection, defects, warranty, and so on. In this section, we will first discuss what types of cost components have been considered. Then, we will discuss the three fundamental pieces of an optimization method: (i) the objective function; (ii) the constraints; and (iii) the solution approach.

### 2.3.1. *Cost components*

Naturally, the manufacturing cost of producing a product is under consideration. If a product is manufactured with a satisfactory quality, then all manufacturing costs will be recovered and the manufacturer will be rewarded with a net profit. For that reason, most of the researchers chose to focus on specific cost components related to quality failures (both internal and external failures) and inspection.

An internal failure cost is incurred when defects are detected and handled prior to shipment to the customers. It is in fact the cost associated with repairing, replacing, or scrapping a defective item. Some papers employed a net profit model and treated a defective item as being of zero value without explicitly mentioning that the item is scrapped; in our classification, we treat this the same as the scrapping cost.

External failure costs result from the repair or replacement of defective products after delivery to the customer. There may also be a certain penalty or fine, as well as expenditure for a recall and for restoring the reputation of the product. The external failure cost is not considered in every publication. Sometimes the outgoing product quality is treated as a constraint (e.g., as in Lindsay and Bishop (1964)) or it is simply assumed that a perfect inspection is performed on every single outgoing product (e.g., as in Tang (1991)). When the external failure cost is indeed considered, some authors assumed that the external cost may depend on the defect type, whereas others assumed no dependence between the external failure cost and the defect type.

The inspection cost includes a fixed amount of capital invested in inspection equipment, and a variable cost that depends on how frequently one actually performs the action of inspection. A vast majority of the researchers used a linear function for the variable inspection cost, i.e., the total variable inspection cost is the number of units inspected multiplied by the inspection cost per unit. A few papers used a quasi-concave function (e.g., as in Britney (1972)) or a general nonlinear function (e.g., as in Ballou and Pazer (1985)) for the inspection variable cost.

In addition to the above-mentioned cost components, two other cost components were also considered: one is the process setup and inventory holding cost, and the other is the cost for searching, and eventually, eliminating the causes of defects.

#### 2.3.2. *Objective function*

In the optimization of the inspection strategy, the most common treatment is to use the total expected cost as the objective function. The expected unit cost, instead of the total cost, is another popular choice as the objective function. However, there are differences in how to count the number of units.

One version is to count all units entering into a production process, i.e.,

$$\textit{objective function} = E\left\{\frac{\textit{total cost}}{\textit{input units}}\right\}, \tag{1}$$

where $E(\cdot)$ is an expectation operator. Given that the number of input units is usually a fixed number, we will put the objective function using the unit cost in the same category as those that use the total cost.

The second version is to count the units leaving a production process, i.e.,

$$\textit{objective function} = E\left\{\frac{\textit{total cost}}{\textit{output units}}\right\}. \tag{2}$$

Equation (2) represents the cost per unit product that is on the market, contrary to the cost per unit product that is processed. If there is no scrapping during production, Equation (2) will be equivalent to Equation (1).

Some authors (e.g. Ballou and Pazer (1982)) have argued that only conforming outgoing units can generate revenue. Thus, they suggested only counting the conforming outgoing units, i.e.,

$$\textit{objective function} = E\left\{\frac{\textit{total cost}}{\textit{conforming output units}}\right\}. \tag{3}$$

However, not all the papers try to minimize the cost. There exist a few papers that choose to maximize the throughput or production capacity. That usually happens when an inspection scheduling problem, in addition to the allocation problem, is being considered.

#### 2.3.3. *Constraints*

The constraints used in the optimization of an inspection strategy arise naturally from the characteristics of the manufacturing system such as the type of production configuration, the type of inspection, and the type of defect. However, authors have also imposed additional constraints when solving for an optimal inspection policy. These constraints include: (i) the Average Outgoing Quality Limit (AOQL) (please refer to Ercan *et al.* (1974) for the definition of AOQL); (ii) a time limit within which the inspection task must finish; (iii) a limit on the number of inspection stations; (iv) a constraint on how many times a measurement can be repeated; (v) a budget limit on manufacturing and inspection actions; and (vi) a lower-bound requirement on throughput or production capacity. Please note that in the above constraints, the limit on the number of inspection stations (constraint (iii)) is actually a special form of the budget constraint (constraint (v)); and the constraint on inspection time (constraint (ii)) is related to the throughput constraint (constraint (vi)).

#### 2.3.4. *Optimization solution approaches*

Almost all of the papers eventually derive a nonlinear function for their total cost functions in which some of the decision variables (such as whether or not to inspect, the serial number of a station, etc.) can only have integer values. For this reason, almost every problem is a NonLinear Programming (NLP) problem, and many of them are also Integer Programming (IP) problems.

A wide variety of optimization methods have been used to solve the resulting optimization problem. We try to classify them into several categories. However, we realize that our categories in Table 2 are not mutually exclusive in the general definition of the listed methods; for instance, we have NLP and IP as two separate categories. We place gradient-based methods for continuous optimization in the NLP category, including those solved through classical optimization algorithms, iterative gradient searches, and experiment-based response surface methodologies (Myers and Montgomery, 1995). On the other hand, we include discrete optimization approaches in the IP category, such as those using the branch-and-bound technique (Raz and Kaspi, 1991).

Probably because of the multistage structure of a manufacturing system, it comes as no surprise that the most popular method used in the literature to solve for an optimal inspection strategy is Dynamic Programming (DP). Indeed, this solution technique is used by 23 papers, accounting for 40% of the 58 papers surveyed. The NLP comes as the second most popular method, used by 13 papers, or 23% of the total.

For an actual manufacturing system, the computations required by DP, IP, or NLP will escalate considerably as the number of stations/stages increases. Their capability in terms of solving a large-scale problem is limited. That is why many kinds of heuristic methods, including random search methods such as Simulated Annealing (SA) and Genetic Algorithms (GAs), are often used to reach a better solution, even though it may not be the optimal one. In fact, heuristic methods are used in 11 papers, making it the third most popular method following DP and NLP. Other optimization methods include those using discrete-event simulations and expert systems.

**Table 2.** Classification of the literature according to modeling characterization

| *Modeling* | *Classification* | *Publications* |
|---|---|---|
| 1. Cost components | Internal failure cost | |
| | Rework/repair | White ('69), Britney ('72), Ercan ('72), Ercan ('74), Trippi ('74), Enrick ('75), Yum ('81), Garcia-Diaz ('84), Peters ('84), Chakravarty ('87), Yum ('87), Tayi ('88), Barad ('90), Kang ('90), Raz ('91), Jewkes ('95), Rebello ('95), Shin ('95), Deliman ('96), Gurnani ('96), Narahari ('96), Viswandham ('96), Chevalier ('97), Chen ('98), Lee ('98), Yao ('99a), Yao ('99b), Zheng ('00), Shiau ('02), Shiau ('03a), Shiau ('03b), Kakade ('04) |
| | Replace | White ('65), White ('69), Ercan ('74), Trippi ('75), Yum ('81), Yum ('87), Barad ('90), Narahari ('96), Shiau ('02), Shiau ('03a), Shiau ('03b) |
| | Scrap | Lindsay ('64), Brown ('68), White ('69), Ercan ('72), Woo ('72), Hurst ('73), Eppen ('74), Ercan ('74), Trippi ('74), Enrick ('75), Ballou ('82), Hsu ('84), Peters ('84), Gunter ('85), Chakravarty ('87), Peters ('87), Yum ('87), Tayi ('88), Barad ('90), Foster ('90), Kang ('90), Raz ('91), Tang ('91), Villalobos ('91), Villalobos ('93), Rebello ('95), Deliman ('96), Viswandham ('96), Chen ('99), Veatch ('00). Shiau ('02), Shiau ('03a), Shiau ('03b) |
| | External failure cost | |
| | Defect type dependent | Trippi ('74), Trippi ('75), Peters ('84), Chakravarty ('87), Rebello ('95), Lee ('98), Yao ('99b), Veatch ('00), Zheng ('00), Kakade ('04) |
| | Defect type independent | Beightler ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Britney ('72), Ercan ('72), Woo ('72), Dietrich ('74), Eppen ('74), Ercan ('74), Enrick ('75), Yum ('81), Ballou ('82), Garcia-Diaz ('84), Hsu ('84), Ballou ('85), Gunter ('85), Yum ('87), Tayi ('88), Barad ('90), Foster ('90), Kang ('90), Raz ('91), Villalobos ('91), Villalobos ('93), Jewkes ('95), Deliman ('96), Viswandham ('96), Chevalier ('97), Chen ('98), Yao ('99a), Shiau ('02), Shiau ('03a), Shiau ('03b), Valenzuela ('04) |
| | Inspection cost | |
| | Fixed cost | Pruzan ('67), White ('69), Trippi ('74), Trippi ('75), Peters ('84), Gunter ('85), Chakravarty ('87), Lee ('87), Peters ('87), Kang ('90), Tang ('91), Chen ('99) |
| | Linear variable cost | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Ercan ('72), Garey ('72), Woo ('72), Hurst ('73), Dietrich ('74), Eppen ('74), Ercan ('74), Trippi ('74), Enrick ('75), Trippi ('75), Yum ('81), Ballou ('82), Garcia-Diaz ('84), Hsu ('84),Peters ('84), Gunter ('85), Chakravarty ('87), Lee ('87), Peters ('87), Yum ('87), Tayi ('88), Barad ('90), Foster ('90), Kang ('90), Raz ('91), Tang ('91), Villalobos ('91), Villalobos ('93), Jewkes ('95), Rebello ('95), Shin ('95), Deliman ('96), Gurnani ('96), Viswandham ('96), Chevalier ('97), Rabinowitz ('97), Chen ('98), Lee ('98), Yao ('99a), Yao ('99b), Veatch ('00), Zheng ('00), Emmons ('02), Shiau ('02), Shiau ('03a), Shiau ('03b), Kakade ('04) |
| | Nonlinear variable cost | Britney ('72), Ballou ('85) |
| | Manufacturing cost | Beightler ('64), Pruzan ('67), White ('69), Garey ('72), Dietrich ('74), Enrick ('75), Peters ('84), Ballou ('85), Chakravarty ('87), Lee ('87), Barad ('90), Kang ('90), Raz ('91), Tang ('91), Rebello ('95), Deliman ('96), Viswandham ('96), Lee ('98), Chen ('99), Veatch ('00), Emmons ('02), Shiau ('02) |
| | Setup and inventory holding cost | Chakravarty ('87), Lee ('87), Tayi ('88), Tang ('91), Jewkes ('95) |
| | Root-cause searching and elimination cost | Lee ('87), Peters ('87), Veatch ('00) |
| 2. Objective function | *E* (total cost) or *E* (cost/input units) | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Britney ('72), Ercan ('72), Garey ('72), Dietrich ('74), Eppen ('74), Ercan ('74), Trippi ('74), Enrick ('75), Trippi ('75), Yum ('81), Garcia-Diaz ('84), Hsu ('84), Peters ('84), Chakravarty ('87), Yum ('87), Tayi ('88), Barad ('90), Foster ('90), Kang ('90), Tang ('91), Villalobos ('91), Villalobos ('93), Jewkes ('95), Shin ('95), Deliman ('96), Viswandham ('96), Chevalier ('97), Chen ('98), Lee ('98), Chen ('99), Yao ('99a), Yao ('99b), Zheng ('00), Emmons ('02), Shiau ('02), Shiau ('03a), Shiau ('03b) |

*(Continued on next page)*

**Table 2.** Classification of the literature according to modeling characterization *(Continued)*

| *Modeling* | *Classification* | *Publications* |
|---|---|---|
| | $E$ (cost/output units) | Gunter ('85), Lee ('87), Raz ('91), Veatch ('00) |
| | $E$ (cost/conforming output units) | Woo ('72), Ballou ('82), Ballou ('85), Peters ('87), Rebello ('95), Kakade ('04), Valenzuela ('04) |
| | Throughput or capacity | Gurnani ('96), Narahari ('96), Rabinowitz ('97) |
| 3. Additional constraints | AOQL | Lindsay ('64), Brown ('68), Ercan ('74), Foster ('90), Viswandham ('96) |
| | Inspection time | Foster ('90), Villalobos ('93), Lee ('98) |
| | Number of inspection stations | White ('69), Trippi ('74), Viswandham ('96), Shiau ('02), Shiau ('03a), Shiau ('03b) |
| | Budget limit | Tang ('91), Rebello ('95) |
| | Number of repeated measurements | Viswandham ('96) |
| | Throughput or capacity | Yum ('87), Shin ('95), Gurnani ('96), Yao ('99a), Valenzuela ('04) |
| 4. Optimization method | Dynamic programming | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Garey ('72), Woo ('72), Eppen ('74), Enrick ('75), Garcia-Diaz ('84), Hsu ('84), Gunter ('85), Chakravarty ('87), Peters ('87), Tang ('91), Villalobos ('91), Villalobos ('93), Gurnani ('96), Chen ('98), Yao ('99a), Yao ('99b), Zheng ('00) |
| | Integer programming | Britney ('72), Ercan ('74), Trippi ('75), Yum ('81), Yum ('87), Raz ('91), Rabinowitz ('97) |
| | Nonlinear programming | Ercan ('72), Trippi ('74), Ballou ('82), Peters ('84), Ballou ('85), Chakravarty ('87), Lee ('87), Tayi ('88), Jewkes ('95), Deliman ('96), Narahari ('96), Chevalier ('97), Lee ('98) |
| | Heuristics | Dietrich ('74), Barad ('90), Foster ('90), Rebello ('95), Viswandham ('96) (using SA and GA), Chen ('99) (using SA), Veatch ('00), Emmons ('02), Shiau ('02), Shiau ('03a), Shiau ('03b), Kakade ('04), Valenzuela ('04) |
| | Simulation | Shin ('95) |
| | Expert system | Kang ('90) |

Using the above modeling characterizations, we classify the existing literature into different categories in Table 2. Similar to Section 2.2, in order to know how a publication models its problem, say, what types of cost components have been considered, one needs to pool the information under different categories.

In Table 2, some categories, for example, the cost components, are not mutually exclusive. Some papers consider all cost components, whereas others consider only a subset. If a paper does not appear under a specific category, it means that the particular cost is not considered by the paper. The categories of linear and nonlinear variable inspection costs are largely exclusive. So are the categories of the objective functions and the optimization methods. The union of linear and nonlinear variable inspection costs covers all the papers with the two exceptions of Narahari and Khan (1996), who assumed the inspection cost to be negligible so that it does not appear in either one of the categories, and Chen and Thornton (1999) who only considered a fixed inspection cost and no variable inspection cost. Hurst (1973) is the only paper not included in either one of the categories under *Objective functions* and *Optimization methods* because it simply presented a modeling process without any detailed optimization formulation or a solution procedure.

## 2.4. *More classifications and discussions*

We have previously classified the inspection strategy into parametric strategies and allocation strategies. When investigating an allocation strategy, Chevalier and Wein (1997) also explicitly studied what specification limits, similar to those used in Statistical Process Control (SPC), should be used in their inspection process to determine whether or not an item or a feature is defective. They labeled this decision as a *testing policy*. This treatment is different from the majority of the surveyed papers, where the authors have assumed either a perfect inspection or an imperfect inspection with a known probability for type-I and type-II errors. Apparently, most authors are indifferent to a testing policy once given the inspection's capability (characterized by the type-I and type-II error probabilities). When a particular set of inspection limits needs to be decided additional complexity indeed comes into play, e.g., the type-I and type-II inspection errors will depend on these specifications. Therefore, we further divide the allocation strategy into two

**Table 3.** Classification of the literature according to the strategy type

| *Parametric strategy (9)* | *Allocation strategy without testing policy (43)* | *Allocation strategy with testing policy (6)* |
|---|---|---|
| Ercan ('72), Ercan ('74), Enrick ('75), Lee ('87), Jewkes ('95), Chen ('98), Yao ('99a), Yao ('99b), Zheng ('00) | Beightler ('64), Lindsay ('64), White ('65), Pruzan ('67), Brown ('68), White ('69), Britney ('72), Garey ('72), Woo ('72), Hurst ('73), Dietrich ('74), Eppen ('74), Trippi ('74), Trippi ('75), Yum ('81), Ballou ('82), Garcia-Diaz ('84), Hsu ('84), Peters ('84), Ballou ('85), Gunter ('85), Chakravarty ('87), Peters ('87), Yum ('87), Tayi ('88), Barad ('90), Foster ('90), Kang ('90), Raz ('91), Tang ('91), Villalobos ('91), Villalobos ('93), Rebello ('95), Shin ('95), Deliman ('96), Gurnani ('96), Narahari ('96), Viswandham ('96), Rabinowitz ('97), Lee ('98), Veatch ('00), Emmons ('02), Kakade ('04) | Chevalier ('97), Chen ('99), Shiau ('02), Shiau ('03a), Shiau ('03b), Valenzuela ('04) |

subcategories: allocation strategies that either do or do not consider the testing policy. Theoretically, the testing policy can also be considered together with a parametric strategy. However, no such incidence was found during our survey.

We are interested in knowing how intensely the different strategies have been studied. Table 3 classifies the literature into each category, where the number in parenthesis in the column header indicates the total number of publications in that category. Clearly, allocation strategies that do not consider the testing policy have been the focus in past investigations. The testing policy was only considered as a part of an inspection strategy in very recent publications, all the relevant papers being published after 1997.

We are also interested in knowing how the number of publications has changed over the past four decades after Lindsay and Bishop first published their seminal paper in 1964. The change is shown using a bar chart in Fig. 3. Figure 3 demonstrates that interest in the area of inspection-oriented quality-assurance strategy has remained relatively constant over the four-decade period at a healthy level of roughly one and a half papers per year. Interestingly, the decade between 1975 and 1984 is the low point and then publications in this area bounce back quite strongly. The most recent decade actually has the strongest publication record, we believe, in part thanks to the wide implementation of in-line quality inspection facilities in various manufacturing environments.

## 3. Diagnosis-oriented sensor-distribution strategy

The primary goal of inspection strategy models is to find the optimal utilization of inspection resources to identify defective parts. That is, the costs to identify and process a defective part are minimized. These models provide solutions to improve the product quality by weeding out potentially defective products before they reach the customers

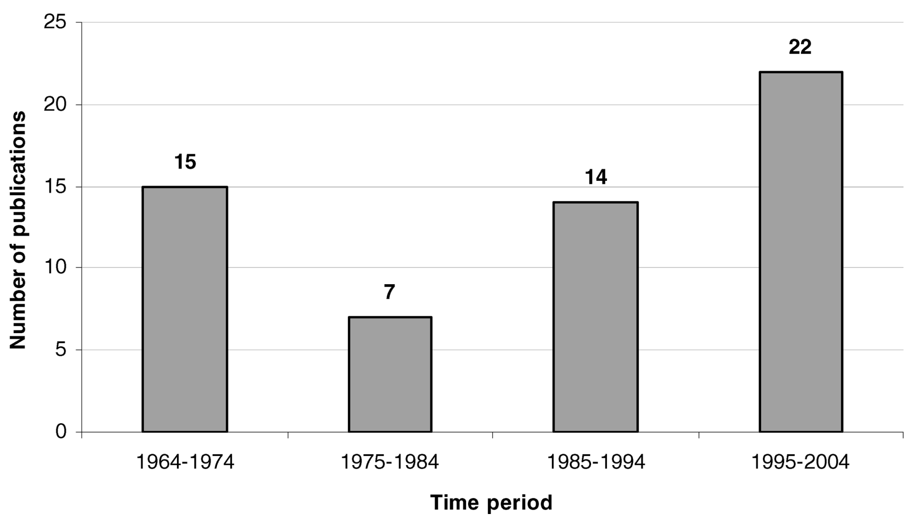


**Fig. 3.** The number of publications on a decade-by-decade basis.

rather than fixing the problem that caused the defect. Following the philosophy behind inspection strategies, if the warranty cost increases drastically, the cost balance will be attained towards a near-zero defect level of product quality. Simply weeding out defective products is not a desirable solution for such a near-zero defect level, since the resulting cost will be too high for any manufacturer to remain competitive in the market place. A strategy to identify and subsequently eliminate major variation sources has to be implemented under the near-zero-defect requirement. This is indeed what has been happening in the past few years; a poor product quality results in extensive warranty costs and the associated negative publicity also tends to hit the company's revenues. Manufacturers are, thus, under great pressure to implement techniques for variation-source diagnosis, mainly through deploying sensors in their production process. This naturally leads to the development of diagnosis-oriented sensor-distribution strategies.

### 3.1. *Problem statement*

In a manufacturing process, sensor distribution involves the determination of: (i) the workstations at which to place the sensing devices; (ii) the number of sensors required at individual stations; (iii) the location of sensors within individual stations.

In the literature, the "location of a sensor" takes two different meanings: the first is the literal meaning of a sensor location, i.e., where a sensor is physically installed; and the second refers to the location of a product feature that a sensor measures. Obviously, the solution of a sensor distribution problem will take quite different routes given the different meanings of the "location of a sensor".

The first meaning, i.e., where to physically install a sensor, is commonly used in computer vision research, where the principal focus is to quantify and understand the relationship between the objects that are viewed and the sensors that observe them (Cowan and Kovesi, 1988; Menq *et al.*, 1992; Tarabanis *et al.*, 1995; Sheng *et al.*, 2003). More specifically, this type of sensor planning problem can be summarized as: "*given information about the environment (e.g., the object under observation, the available sensors) as well as information about the task that the vision system is to accomplish (i.e., detection of certain object features, object recognition, scene reconstruction, object manipulation), develop strategies to automatically determine sensor locations that achieve this task with certain degree of satisfaction*" (Tarabanis *et al.*, 1995). In the computer vision approaches, the set of product quality features to be measured is usually assumed to be known.

The second meaning of sensor location, i.e., which product feature to measure, is more commonly used in quality control research. Under this meaning, distributing sensors is, in fact, equivalent to selecting product features to measure on different stations in a manufacturing process. The reason is obvious: in order to track down the underlying root causes, it is crucial to select a set of product features, the measurement of which can lead, in some optimal sense, to an inference about the causes of the variations. In contrast, the computer vision approaches, that are based on the first meaning, do not go all the way to the inference-making stage which allows us to ultimately diagnose the variation sources.

The computer vision approaches were apparently the first to be considered. For this reason, when taking the second meaning, people tend to assume the availability of a computer vision method that can decide the location where the sensors are physically installed. The relevant publications on computer-vision-based sensor planning have been nicely summarized in the survey by Tarabanis *et al.* (1995); for more recent publications after 1995, please refer to Sheng *et al.* (2003). In this survey, our principal focus is on research that has taken the second meaning, which decides the distribution of sensors that are taken in an abstract sense. Please note that a set of publications targeting geometric tolerance verification for complicated surfaces (e.g. Menq *et al.* (1992)) also bears a certain similarity to the surveyed approach. However, the research objective for tolerance verification is different from that of root-cause diagnosis and their approaches are typically based on statistical sampling theory (Cochran, 1977); please refer to Dowling *et al.* (1997) for a review on the feature or measurement point selection approaches used in tolerance verification. We have choosen not to include publications from the tolerance verification research in this survey.

Similar to how we classified the inspection strategy in Section 2, we will discuss system characteristics and modeling characteristics in Sections 3.2 and 3.3, respectively. Somewhat different from the studies in Section 2, in a sensor-distribution study, sensors are generally treated as in-process automated devices, which can operate continuously at a comparatively low incremental cost. Moreover, the resulting sensor distribution is almost always determined before a production process is built.

### 3.2. *System characteristics*

The physical system, including both manufacturing and measurement operations, is characterized through three aspects: (i) process configuration; (ii) the sensor system homogeneity; and (iii) variation sources.

#### 3.2.1. *Process configuration*

If using the classification from Fig. 2(a–c), the process configuration considered in the sensor-distribution strategy is no more complex than a serial system. Still, three distinctions are made: (i) single station: there is only one manufacturing station; (ii) end-of-the-line sensing: the sensing station is limited to be at the end of the production line but the variation sources include those from upstream stations; and (iii) distributed sensing: multiple workstations constitute a serial production system and the sensing stations could be located in multiple pre-selected places in the production line.

3.2.2. *Sensor system homogeneity*

A sensor capability is typically characterized through the bias and uncertainty of its measurements. Since all the sensors are calibrated before service, it is commonly assumed that a sensor should be able to provide an unbiased measurement, i.e., the sensor noise $\varepsilon \sim N(0, \sigma^2)$, where $\sigma^2$ is the variance. When multiple sensors are deployed, a sensor system can be generally distinguished, being either a *homogeneous* or a *heterogeneous* sensor system. A homogeneous sensor system assumes that all the sensors are identical. Their sensor noises are independent and are of equal variance, i.e., $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma^2 \mathbf{I})$, where $\boldsymbol{\varepsilon}$ is the vector of noises from all the sensors and $\mathbf{I}$ is an identity matrix. Of course, no actual sensor system is absolutely homogenous since no two sensors are identical. However, a sensor system using the same type of sensor units from the same manufacturer and at the same stage of their service life may reasonably qualify as a homogeneous sensor system. On the other hand, a heterogeneous sensor system consists of sensors that have different statistical properties, violating the assumption that $\boldsymbol{\varepsilon} \sim N(0, \sigma^2\mathbf{I})$. For a sensor system constituted by different types of sensors, or even the same type of sensor but at different stages of their service lives, using a heterogeneous sensor model would be more reasonable.

3.2.3. *Variation sources*

First, we denote by $\mathbf{u}$ the process variables representing the variation sources. Because $\mathbf{u}$ is usually not directly measurable, an inference regarding $\mathbf{u}$ will be made based on sensor measurements. In the SPC literature, a special case is often modeled using the first two moments of a random process, i.e., a mean shift, a variance change, or a combination of both. Following the same spirit, the variation sources are the *mean* and *variance components* associated with $\mathbf{u}$. If $\mathbf{u}$ is an autocorrelated process, certain dynamic patterns could be important in understanding why the process has gone wrong. For this reason, some publications also use the estimation of $\mathbf{u}$ itself, denoted by $\hat{\mathbf{u}}$, as the variation-source variable.

Apparently, the system characteristics studied in sensor-distribution research are quite different from those in the inspection-strategy study. The sensor-distribution research seemingly studies a simpler process configuration than does the inspection strategy. However, in a general sense, the sensor-distribution strategy gets closer to the real physics and the actual measurements of a manufacturing processes. For instance, the quality measure is no longer dichotomous. Rather it involves estimations and statistical inferences based on the continuous measurement values. The sensor system capability is measured by its accuracy and precision that can be obtained from a gauge in a repeatability and reproducibility study instead of some arbitrarily assigned type-I and type-II errors. For the description of a defect, a sensor-distribution study associates variation sources with the statistical properties of process variables that have more explicitly physical meaning, whereas the defects in the inspection-strategy study are associated with nothing more specific than an occurrence probability. The difference in system characteristics in the two studies is summarized in Table 4.

The sensor distribution publications are classified in Table 5 in terms of system characteristics. Most of the earlier approaches focused on diagnosing faults occurring at a single station. The single-station model has been mainly studied in two contexts: (i) sheet metal or autobody assembly; and (ii) workpiece localization. Khan *et al.* (1998) extended the sensor-placement problem to an end-of-the-line sensing. Khan and Ceglarek (2000) also studied the distributed sensing configuration, which is the focus of most of the recent studies (Ding *et al.*, 2003; Djurdjanovic and Ni, 2004).

Fewer studies on heterogeneous sensor systems are found than those on homogeneous sensor systems. Some papers do not appear in either category of sensor system homogeneity in Table 5 (for example the papers of Weill *et al.* (1991) and Hu (1997)) because no explicit characterization of the sensor noise was attempted. Another set of pure modeling papers (for example that of Jin and Shi (1999)) either do not specify the sensor noise structure or do not explicitly utilize the specified sensor noise structure for the purpose of diagnosis, estimation, or sensor placement. Since the implication of sensor system homogeneity is vague under those circumstances, we do not include those modeling papers in either category.

The papers classified under homogeneous sensor system also include those utilizing the ordinary least squares approach in their diagnosis and estimation efforts (e.g.,

**Table 4.** Difference of system characteristics in the two studies

| *System characteristics* | *Inspection strategy* | *Sensor distribution strategy* |
|---|---|---|
| Product quality | Dichotomous | Continuous |
| Process configuration | Serial, assembly, and nonserial | No more complex than serial |
| Characterization of inspection or sensor | Fraction, repeated, or dynamic inspection<br>Type-I and type-II errors | Sensor accuracy and precision<br>Homogeneous and heterogeneous sensor system |
| Defect behavior | Defect type, occurrence probability, and defect reparability | Mean and variance components, estimation of process variables |

**Table 5.** Classification of the literature according to system characterization

| *System characterization* | *Classification* | *Publications* |
|---|---|---|
| 1. Production configuration | Single station | Weill ('91), Hu ('92), Ceglarek ('96, '99), Apley ('98), Chang ('98), Khan ('99), Wang ('99), Carlson ('00), Rong ('00, '01), Camelio ('03b, '04), Liu ('04), Zhu ('04) |
| | End-of-the-line sensing | Hu ('97), Khan ('98), Mantripragada ('99), Suri ('99), Apley ('01, '03), Ding ('02a), Carlson ('03) |
| | Distributed sensing | Jin ('99), Khan ('00), Djurdjanovic ('01, '03, '04), Ding ('02b, '03, '04a), Huang ('02, '04), Camelio ('03a), Zhou ('03a, '03b), Apley ('04) |
| 2. Sensor system homogeneity | Homogeneous | Ceglarek ('96), Apley ('98, '01, '03, '04), Chang ('98), Khan ('98, '99, '00), Suri ('99), Wang ('99), Carlson ('00, '03), Rong ('00, '01), Ding ('02b, '03, '04a), Huang ('02, '04), Camelio ('03b, '04), Djurdjanovic ('03, '04), Zhou ('03a), Liu ('04), Zhu ('04) |
| | Heterogeneous | Ceglarek ('99), Ding ('02a), Apley ('04) |
| 3. Variation sources | Mean components | Jin ('99), Carlson ('00), Djurdjanovic ('01), Huang ('02, '04), Camelio ('03a), Zhou ('03a, '03b), Liu ('04) |
| | Variance components | Hu ('92, '97), Ceglarek ('96,'99), Apley ('98, '01, '03, '04), Khan ('98, '99, '00), Jin ('99), Suri ('99), Carlson ('00, '03), Rong ('00), Djurdjanovic ('01, '03, '04), Ding ('02a, '02b, '03, '04a), Huang ('02, '04), Camelio ('03a, '04), Zhou ('03a, '03b), Liu ('04) |
| | $\hat{\mathbf{u}}$ | Weill ('91), Chang ('98), Mantripragada ('99), Wang ('99), Rong ('01), Camelio ('03b), Zhu ('04) |

Wang and Nagarkar (1999) and Camelio *et al.* (2003b)). This is because optimal estimation using an ordinary least squares approach can be performed only under the condition that $\varepsilon \sim (0, \sigma^2\mathbf{I})$, according to the Gauss-Markov Theorem.

A few other papers, although starting with a general covariance matrix $\mathbf{\Sigma}$ for the sensor noise, eventually do away with the general noise structure by assuming that the noise covariance matrix is known. Then, after pre-multiplying the model by $\mathbf{\Sigma}^{-1/2}$, the general structured $\mathbf{\Sigma}$ is transformed into an identity matrix (Apley and Shi, 1998; 2001). Therefore, those papers that assume a complete knowledge of the noise (Djurdjanovic and Ni, 2003; Huang and Shi, 2004), are included in the category of homogeneous sensor systems.

There have been very few attempts to study diagnosability in a heterogeneous sensor system. Ceglarek and Shi (1999) assumed a homoscedastic and uncorrelated measurement noise for the most part of their paper but they did provide a simulation case study in which their approach was extended to the heteroscedastic and uncorrelated sensor noise case. The studies of Ding *et al.* (2002a) and Apley and Ding (2004) are applicable to a general structure of the noise covariance matrix and remain valid for the heteroscedastic and correlated case.

The majority of the surveyed studies were interested in estimating *variance components*, as opposed to *mean components*. In fact, we observed that those papers that did investigate mean components also studied variance components. On the other hand, there exist dedicated approaches (for example that of Ceglarek and Shi (1996)) to variance components. This is probably because detecting, identifying, and ultimately, eliminating the root causes of random process variation is a greater challenge than compensating a mean shift. Moreover, a sustained, consistent deviation from nominal values (i.e., a mean shift) can often be compensated relatively easily by process engineers via shimming and other adjustments. In contrast, variation is much more difficult to compensate and requires either some form of on-line feedback control or the removal of the variation root cause(s).

### 3.3. *Modeling characteristics*

There are four issues to be addressed in a sensor-distribution study: (i) a model that represents the effects of the variation sources on the sensor data, labeled as a quality-fault model by Zhou *et al.* (2003a); (ii) a performance measure to benchmark the effectiveness of a sensor system; (iii) optimization formulations including the objective function and constraints; and (iv) an optimization solution approach to solve for the optimal strategy. Compared with the modeling approaches used in the inspection strategy study, the quality-fault model is a unique component in the sensor-distribution study. Component (ii), the performance measure of a sensor system, is also unique here because the inspection strategy study usually needs no further analysis after assuming the type-I and type-II error probabilities for an inspection action. Components (iii) and (iv) are common to both studies but the details are different as will be seen in the following.

#### 3.3.1. *Quality-fault model*

A linear structured model is often used to link sensor measurements to variation sources because the deviation of product/process features is usually much smaller than the nominal values in quality control application. A linearization of nonlinear systems can provide a reasonable representation of the quality-fault relationship in discrete-part manufacturing processes. There are two versions of the linear-structured model, for the single station and the multiple station process configurations, respectively. For a single station, a simple linear model can be expressed as:

$$\mathbf{y}(t) = \mathbf{A}\mathbf{u}(t) + \mathbf{v}(t), \quad t = 1, 2, \ldots, M, \tag{4}$$

where $\mathbf{y}(t)$ is a vector of $n$ measured product features, $\mathbf{u}(t) = [u_1(t), u_2(t), \ldots, u_p(t)]^T$ is a random vector whose elements are associated with $p$ independent variation sources, $\mathbf{v}(t)$ is an additive sensor noise vector, $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \ldots, \mathbf{a}_p]$ is an $n \times p$ diagnostic matrix relating the variation sources to the measurement vector, $t$ is an observation index, and $M$ is the sample size. The quantity $\mathbf{a}_i u_i(t)$ represents the effects of the $i$th variation source on the measurements for part number $t$ of the sample. Sensor deployment information (such as the number and positions of sensors) is included in matrix $\mathbf{A}$.

For a multiple-station process, a recursive station-indexed state space model is often used to link the variation sources from individual stations to the sensor measurements. The state space model generally reads as:

$$\mathbf{x}_k = \mathbf{A}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k \quad \text{and} \quad \mathbf{y}_k = \mathbf{C}_k\mathbf{x}_k + \mathbf{v}_k, \quad k = 1, \ldots, N, \tag{5}$$

where the subscript $k$ is the index of a station and $N$ denotes the total number of stations; $\mathbf{x}$ is the process-quality state variable, and $\mathbf{w}$ is the process background disturbance; $\mathbf{A}_{k-1}\mathbf{x}_{k-1}$ represents the transformation of quality deviation from station $k-1$ to station $k$, $\mathbf{B}_k\mathbf{u}_k$ represents quality deviations resulting from variation sources at station $k$, and $\{\mathbf{C}_k\}_{k=1,\ldots N}$ includes the sensor distribution information throughout a process ($\mathbf{C}_j = 0$ if no measurement is taken on station $j$); finally, sample index $t$ could be, but is not, explicitly included here. This model can be used for both the end-of-the-line sensing, where the only nonzero $\mathbf{C}$ matrix is $\mathbf{C}_N$, and distributed sensing, where one needs to decide the optimal set of nonzero $\mathbf{C}$ matrices as well as the sensor distribution within each station.

This station-indexed state space model has been used to model quality propagation in various multistation manufacturing processes, e.g., the rigid-part assembly process (Jin and Shi, 1999; Mantripragada and Whitney, 1999), the compliant-part assembly process (Camelio *et al.*, 2003a), the machining processes (Djurdjanovic and Ni 20001; Huang *et al.*, 2002; Zhou *et al.* 2003b; Huang and Shi, 2004), and the sheet stretch forming processes (Suri and Otto, 1999).

#### 3.3.2. *Performance measure of a sensor system*

The following performance measures have been reported in the literature for sensors on a single station or those distributed in a production line: (i) diagnosability; (ii) accuracy or sensitivity; and (iii) the minimum distance between variation patterns. Diagnosability is a mathematical condition under which the mean and/or variance components are uniquely identifiable. This is analogous to the issue of singularity in a standard least squares approach that results in nonunique parameter estimates and it typically involves checking whether a certain matrix (called the diagnosability matrix) is singular (Ding *et al.*, 2002b; Zhou *et al.*, 2003a).

The estimation uncertainty of mean and variance components is used as the accuracy index. The alphabetic optimality criteria such as the $D$-optimality, the $A$-optimality, and the $E$-optimality, which were originally developed in research on optimal experimental design (Fedorov, 1972; Atkinson and Donev, 1992), are often adopted in sensor distribution studies. They involve the optimization of a certain measure of the Fisher information matrix $\mathbf{M}$. The $D$-optimality maximizes the determinant of $\mathbf{M}$, or equivalently, the product of all eigenvalues associated with $\mathbf{M}$; the $A$-optimality maximizes the summation of all eigenvalues of $\mathbf{M}$, and the $E$-optimality maximizes the smallest eigenvalue of $\mathbf{M}$. The accuracy index is also known as the sensitivity index, i.e., how sensitive a sensor system is with respect to the change of variation sources. Liu *et al.* (2004) showed that the sensitivity index is equivalent to the estimation accuracy of variation sources under a normal process condition.

Some publications have based their variation diagnosis algorithms on a pattern matching procedure (including those of Ceglarek and Shi (1996); Khan *et al.* (1998); Khan *et al.* (1999); Khan and Ceglarek 2000). The pattern matching procedure also uses the quality-fault model as previously outlined but it needs to define a set of patterns associated with each variation source. From the actual measurement data collected during production, a symptom vector is extracted, and then, the symptom vector is compared with the variation patterns. Finally, the variation sources are identified if a match is found. The performance measure of such a sensor system is usually based on the distance among the variation pattern vectors, e.g., maximizing the minimum pattern distance. The larger the distance is, the better a sensor system can perform variation diagnosis. This performance measure is actually similar to the $E$-optimality.

The general concept of all the above performance measures is equally applicable to mean components, variance components, and $\hat{\mathbf{u}}$, however, the corresponding diagnosability matrix or Fisher information matrix may be different.

#### 3.3.3. *Optimization formulation*

There are generally three types of problems considered in the literature: (i) for a given number of sensors, find the optimal sensor locations; (ii) find the minimal number of sensors as well as the corresponding locations; and (iii) given the distribution of $q$ sensors, where to distribute the additional $s$ sensors? For the first problem, the optimization formulation will be

F1 Objective function: optimize one of the performance measures of a sensor system subject to the geometry and physical constraints for sensor locations, i.e., where a potential sensor can be located.

In this formulation, since the sensor number is given, cost components are not directly considered.

The second problem involves a trade-off among costs. Since an increase in sensor numbers will generally result in a better system performance (diagnosability or accuracy) but at the price of a higher sensor cost, people usually try to reach a cost balance between the benefit gained from a better system and the cost of more sensors. In a sensor-distribution study, a variable sensor cost is not usually considered, since an automated sensor device has a very low operating cost. The costs associated with quality failure are purposely left out because of the study's original intent. Then the overall cost is the summation of a positive fixed sensor cost and a negative cost from an increased diagnosis capability. The optimization formulation in this case is then

F2 Objective function: minimize the total cost subject to geometry and physical constraints for sensor locations.

Since it is difficult on many occasions to quantify the monetary saving associated with an improved sensor system, people would rather use the performance measure as a constraint, while minimizing the sensor cost, or equivalently the sensor number, i.e.

F3 Objective function: minimize the sensor cost (or the sensor number) subject to a requirement on the performance measure as well as the geometry and physical constraints for sensor locations.

The third problem only differs from the first by the fact that $q$ sensors are already in place and we can only manipulate the locations and number of additional sensors. It will eventually use one of the above three formulations, depending on whether or not the number of additional sensors is given.

3.3.4. *Optimization solution approach*

The formulations F1 to F3 will lead to a constrained nonlinear optimization problem. The optimization methods explored in the literature include: Powell's direct search (Wang and Nagarkar, 1999), sequential quadratic programming or gradient-based search (Khan *et al.*, 1999), exchange algorithms (Camelio *et al.*, 2003b; Liu *et al.*, 2004), and GAS (Djurdjanovic and Ni, 2004).

Interestingly, DP, the most popular solution tool in inspection strategy studies is rarely used in the sensor distribution literature. We note that the performance measure of a sensor system, no matter whether it is in the objective function or in the constraints, is generally impossible to decompose into additive components and thus be associated with individual segments of a multistage process. This property prevents the optimization problem for sensor distributions from being formulated as a DP problem. Thus, DP is not an attractive tool to solve a sensor distribution problem.

The publications are summarized in Table 6 using the categories of the modeling characteristics. One may note that the number of publications appears to be decreasing from top down in Table 6. This is due to the fact that some of the papers only studied the quality-fault model without mentioning the performance measure and optimization, and some others only considered the performance measure with no optimization. On the other hand, a publication can also appear in multiple sub-categories associated with the same characterization if it addresses multiple issues related to a sensor-distribution problem. For instance, Wang and Nagarkar (1999) considered both the problem of finding the sensor locations for a given number of sensors and the problem of deciding the sensor location and number simultaneously. They proposed a two-level hierarchical approach when solving the problems. That is why this paper appears in two sub-categories in both the *Optimization formulation* and *Solution methods* categories.

## 4. Discussions and thoughts on future research

Based on the discussions in Section 2, we observe that inspection strategies have been studied in a rather comprehensive fashion. On the other hand, research on sensor distribution is relatively recent. For instance, strategies explicitly designed for distributed sensing in a multistation process are still in their early stages of development. Another example is that, although heterogeneous sensor systems have been modeled and characterized, no systematic approach towards a distribution strategy for such a heterogeneous system has yet been reported.

As explained in Section 1, inspection strategies and sensor distribution strategies focus on different aspects of a practical problem. An inspection strategy is a high-level operational strategy after simplifying and parameterizing system details such as the defect characterization or the inspection capability. A sensor distribution study uses physically meaningful variables and parameters but the insight from its solution do not constitute a high-level operational strategy in a complicated manufacturing environment.

Combining the strengths of the two approaches may produce additional benefits, including that: (i) an integrated model could be more realistic when certain assumptions are relaxed; (ii) the data-driven statistical approach in a sensor-distribution study may provide a means to estimate the parameters used for the inspection study; and (iii) a combined strategy should be more capable of handling decision-making in both detailed and high level operations.

**Table 6.** Classification of the literature according to modeling characterization

| *Modeling* | *Classification* | *Publications* |
|---|---|---|
| Quality-fault model | Single station | Weill ('91), Hu ('92), Ceglarek ('96, '99), Apley ('98, '01, '03), Chang ('98), Khan ('99), Wang ('99), Rong ('00, '01), Camelio ('03b, '04), Liu ('04), Zhu ('04) |
| | Multiple station | Hu ('97), Khan ('98, '00), Jin ('99), Mantripragada ('99), Suri ('99), Carlson ('00, '03), Djurdjanovic ('01, '03, '04), Ding ('02a, '02b, '03, '04a), Huang ('02, '04), Camelio ('03a), Zhou ('03a, '03b), Apley ('04) |
| Performance measure | Diagnosability | Ding ('02b, '03), Zhou ('03a), Apley ('04) |
| | $A$-Optimality | Djurdjanovic ('03, '04), Zhu ('04) |
| | $D$-Optimality | Wang ('99), Camelio ('03b), Djurdjanovic ('03) |
| | $E$-Optimality | Djurdjanovic ('03), Ding ('04a), Liu ('04) |
| | Pattern distance | Khan ('98, '99, '00), Ding ('02a) |
| Optimization formulation | Given number, find location | Khan ('98, '99, '00), Wang ('99), Camelio ('03b), Ding ('03), Zhu ('04) |
| | Find both number and location | Wang ('99), Djurdjanovic ('04), Liu ('04) |
| | Add additional sensors | Ding ('04a) |
| Solution methods | Direct search | Wang ('99) |
| | Sequential quadratic programming or gradient-based search | Khan ('98, '99) |
| | Exchange algorithms | Wang ('99), Khan ('00), Camelio ('03b), Ding ('03, '04a), Liu ('04), Zhu ('04) |
| | Genetic algorithms | Djurdjanovic ('04) |

Certainly the methodology for the integration is going to be quite challenging, primarily because the two studies adopt fundamentally different modeling approaches. Also there is a dearth of capable methods that can readily solve a combined problem, which will be a mix of continuous and discrete variables and will have a relatively large scale. The following are a few examples of areas in which we feel that the integration of existing methodologies may be beneficial.

### 4.1. *Using a continuous quality level*

All the inspection strategy studies assume a dichotomous quality level. However, most of the in-process sensors give continuous measurements that are contaminated with sensor noises. Simply transforming these data into a binary output, i.e., defective or nondefective, may result in a loss of information contained in the original measurements. Defining a continuous quality level and connecting it with an inspection or sensor-distribution policy may better facilitate quality control efforts and improve the capability of root-cause diagnosis. In fact, during the study of an allocation strategy with the testing policy Chevalier and Wein (1997) used a measurement error model. The measurement error model is actually a special form of Equation (4) after setting $\mathbf{A} = \mathbf{I}$. We consider it to be one of the early efforts in extending beyond the dichotomous quality level. In future work, a generic quality-fault model should be used so that inferences can be made regarding changes in the underlying process variables.

### 4.2. *Adaptive strategy for sensor distribution*

The current sensor-distribution strategies are predetermined. In light of the fact that wireless mobile sensors are becoming more and more realistic, an adaptive strategy for sensor distribution seems to be required. An adaptive strategy will decide when a dormant wireless sensor will be activated or a measurement-taking action should be taken based on the outcomes of previous inspections or measurements. Such an adaptive strategy is particularly meaningful for a wireless sensor network, where the energy consumption is a major concern and thus sensor nodes will usually have to work in a low-power regime unless being actively utilized. Again, in inspection strategy studies, some adaptive strategies have been investigated (Dietrich and Sanders, 1974). Recently Priebe *et al.* (2004) proposed a framework for adaptive sequential sensing and processing in classification applications. It is now time to expand the existing adaptive methodologies to sensor distribution applications, especially, those in a wireless network setting.

### 4.3. *A more realistic quality-fault model*

Apparently, a linear quality-fault model working only for a serial production system is not very realistic in actual manufacturing settings. Convergent and other nonserial production systems have been investigated in inspection strategy studies. These initial footsteps may be followed to expand the quality-fault model into sensor distribution studies. Another issue is related to the validity of the linear model structure used to represent the quality-fault relationship. In a general discrete-part manufacturing process, although linearization is a reasonably good approximation for every single operation, the nonlinear effect of error propagation could become significant in a process consisting of a large number of stations and operations. Using a nonlinear model could make the analysis and design highly complex and thus sometimes a piecewise linear model may be a good trade-off between having a realistic model and problem tractability.

We would also like to note that current studies on inspection and sensor-distribution strategies by and large assume that the sensor itself will function as it is intended. Although a sensor noise model is used, either as a type-I and type-II error model or as a statistical variation model, the critical issue of what if the sensor deteriorates or even malfunctions has not been thoroughly studied. The sensor degradation effect will likely manifest itself in a time-varying fashion, which perhaps makes a challenging problem even more difficult. To that end, we believe that robust or fault-tolerant strategies are much needed to offset any possible adverse effects caused by sensor anomalies.

As a final note, we feel that there are many open areas and opportunities for future development in the study of sensor-distribution strategies since it is a relatively new area. We also note that the most recent development in this area is the emergence of the distributed wireless sensor network, which has been identified by MIT's *Technology Review* as one of the top ten emerging technologies that will change the world (Anon, 2003). This new technology has generated considerable excitement and is attracting serious attention. We would like to direct interested readers to Ding *et al.* (2004b), which presents a lot more discussion on research challenges and opportunities related to this new area.

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