Integration of Process-Oriented Tolerancing and Maintenance Planning in Design of Multistation Manufacturing Processes

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***Abstract*—Manufacturing systems are inherently imperfect both statically and dynamically. Tolerance and maintenance design are two major tools to address the static and dynamic imperfection of manufacturing processes (i.e., inherent process imperfection and tooling deterioration, respectively). Yet, traditionally, tolerance and maintenance designs have been studied separately to address these two critical areas of manufacturing systems. This paper presents an integrated framework of tolerance and maintenance design for multistation manufacturing processes. Two nonlinear optimization problems are formulated to minimize the overall average production cost in the long run, which includes the tolerance cost of tooling fabrication, maintenance cost, and the overall loss of quality (as a part of the objective function or as a constraint function). The proposed methodology is illustrated, analyzed, and further discussed in the context of a multistation automotive body assembly process. Extensive numerical analyses are conducted to demonstrate the efficiency of the developed methodology. Given various cost components and time horizons, the integrated design scheme is compared with traditional design schemes in terms of cost efficiency, offering new insights into the interrelation between manufacturing process maintenance and tolerancing in the context of the product life cycle.**

***Note to Practitioners*—With intensified competition as a result of economic globalization, quality and cost have become crucial factors to the success of any manufacturing industry. Decisions in the process design phase, such as process tolerance assignment and maintenance planning, play a substantial role for overall manufacturing quality and costs. Tolerance of process variables determines the inherent variation level of a manufacturing process. Preventive maintenance oversees and controls process degradation and its resulting deterioration on product quality. Significant tooling and operational costs result from both tolerancing and maintenance activities. Traditionally, tolerancing and maintenance decision-making have been studied separately. Tolerancing was mainly conducted during the design stage; while maintenance policy was often determined after a manufacturing system was designed and installed. However, tolerancing of process variables and maintenance decision-making policy are interconnected in modern manufacturing systems. Intuitively, tight initial tolerances specified on process variables are able to reduce the frequency of conducting maintenance during production, since the process can accommodate more deterioration to reduce maintenance cost; but they take a toll on tolerance cost. On the other hand, loose initial tolerances specified on process variables can lower design cost but increase the frequency of maintenance during production. Hence, there is a critical need to strike a balance between the tolerance cost of tooling fabrication and the maintenance cost of tooling replacement. This paper presents a new framework to integrate tolerance design and maintenance planning for multistation manufacturing processes. Optimization problems are formulated to minimize the overall production costs including tooling costs, maintenance costs, and quality loss. The proposed framework is illustrated in the context of automotive body assembly processes. When compared to other separated designs, this integrated design methodology leads to more desirable system performance with a significant reduction in production cost.**

***Index Terms*—Multistation manufacturing processes, preventive maintenance, process-oriented tolerancing, quality loss.**

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I. Introduction

Manufacturing processes built within design specifications are inherently imperfect in fabricating products. Additionally, they deteriorate during the system's life cycle. In order to improve the performance of manufacturing systems, two separate approaches, namely tolerancing and maintenance, have been extensively studied to address these problems. Tolerance design allocates an acceptable range of process parameter variation, thereby determining the initial performance conditions of manufacturing systems. On the other hand, maintenance policy is used to periodically restore the deteriorated manufacturing system to conditions determined by the initial tolerance design, thus controlling the dynamic performance of the manufacturing system. These two phenomena and the corresponding problem-solving approaches are shown in Fig. 1.

Traditionally, tolerancing and maintenance decision-making have been studied separately. Tolerancing was mainly conducted during the process design stage; while maintenance policy was often determined after a manufacturing system is designed and installed. A significant amount of research exists in each of these separate areas. These research works have been thoroughly surveyed by Valdez–Flores and Feldman [1], Pierskalla and Voelker [2], Elsayed [3], and Takata *et al.* [4] for maintenance decision-making; and by Chase and Parkinson

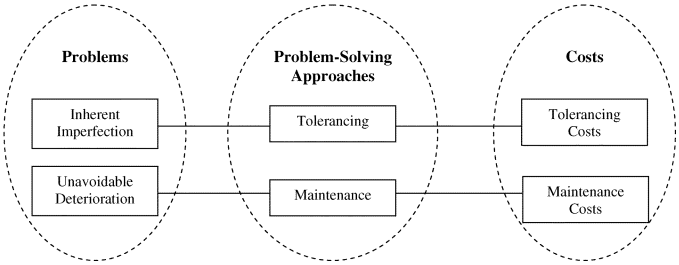

Fig. 1. Methodologies of improving manufacturing systems' performance.

[5], Roy *et al.* [6], Voelcker [7], and Hong and Chang [8] for tolerance design and analysis.

In general, maintenance methodologies can be divided into: 1) reactive maintenance; 2) preventive maintenance; and 3) predictive maintenance. Reactive maintenance is a fix-upon-failure approach. Preventive maintenance is a preplanned maintenance schedule in accordance with the failure prediction given by a system reliability model. Predictive maintenance can be considered as condition-based preventive maintenance (i.e., the maintenance schedule will be updated based on the online measurement of process conditions). Predictive maintenance requires direct and frequent observations of the states of all system components. In discrete-part manufacturing processes, direct online measurements of tooling elements are often extremely costly. For example, in the current auto-body assembly processes, direct and frequent measurements of all locators are not always feasible. Therefore, in this paper, we focus on preventive maintenance policies in discrete part manufacturing processes with reactive maintenance upon the unexpected catastrophic failures of tooling elements.

Hong and Chang [8] classified the existing tolerance research into seven categories: 1) tolerance schemes; 2) tolerance modeling and representation; 3) tolerance specification; 4) tolerance analysis; 5) tolerance synthesis or allocation; 6) tolerance transfer; and 7) tolerance evaluation. Among them, tolerance synthesis is a method which allocates the final product/assembly tolerances to the individual component tolerances. The tolerancing problem investigated in this paper is a tolerance synthesis problem. The majority of tolerance synthesis research is based on optimization methods [9]–[11]. In recent years, methods of quality engineering, such as quality loss function and the process capability index, have been used in tolerance research [12]–[14]. As pointed out in [8], a major drawback of most tolerance synthesis models is that they try to take advantage of the superficial knowledge of processes. Meaningful tolerance values cannot be provided unless the analysis is carried out on how the parts are actually manufactured. Several researchers have investigated the design of optimal processes and optimal component tolerances at the same time [15]–[18]. Certain recent tolerancing models also capture manufacturing cost, quality loss, and scrap/rework cost [19]–[23]. A dynamic tolerance analysis approach has been proposed qualitatively in [24] to take into account the functional degradation in tolerance analysis. It was also suggested in [24] that dynamic tolerance "forms the basis for design for maintainability and model-based maintenance." According to the classification put forth [8], the research of transferring tolerance requirement from the (product) design stage to the manufacturing stage is tolerance transfer [25]–[27], which takes into account machining errors, setup errors, tool wears, etc. However, based on our review of the existing tolerance transfer literature, to date, important issues in manufacturing, such as tool wear and tool maintenance, have not been addressed quantitatively.

Recently, new tolerancing research called process-oriented tolerancing was proposed [28]. Process-oriented tolerancing is essentially a tolerance transfer research based on tolerance synthesis approaches. That is, the quality specification of the final product is ensured by optimally allocating tolerances of process variables, such as fixturing errors in assembly processes, tooling vibration in machining processes, and punch speed in stamping processes, respectively. Process variables are not part of product information but descriptions of the states of the manufacturing system. Variations of process variables have a significant influence on product quality loss in complex manufacturing systems [29].

The issue of process-oriented tolerancing was explored for a class of multistation manufacturing processes (MMP), which involve multiple stations and/or operations to produce a product [28], [30]. A major obstacle identified toward the development of process-oriented tolerancing is the lack of a system model that can describe the impact of process variables on product quality at a system level. The recent development of a stream-of-variation modeling approach [31]–[37] defines relations between the variation of process variables and product quality for MMPs, thus providing the opportunity to optimally allocate tolerances to process variables. Ding *et al.* [28] also pointed out that "process variables carry the dynamic process information such as tooling degradation and, thus, they are strongly related to process reliability and the corresponding maintenance policies." This suggests that tolerance design and maintenance decision-making policy are interconnected through process variables. Intuitively, tight initial tolerances specified on process variables are able to reduce the frequency of conducting maintenance during production, because the process can accommodate more deterioration to reduce maintenance cost; but they take a toll on tolerance cost. On the other hand, loose initial tolerances specified on process variables can lower design cost but increase the frequency of maintenance during production. Hence, there is a critical need to strike a balance between the tolerance cost of tooling fabrication and the maintenance cost of tooling replacement. However, the maintenance schedule in [28] is not considered as a decision variable but is a predetermined constant period based on empirical experience.

To some degree, the design philosophy separating tolerancing and maintenance follows a "design it now and fix it later" approach [36], which is not cost-effective. The integrated design of tolerance and maintenance policy has the potential to significantly reduce the overall production cost when compared to traditionally separated design philosophy. Another advantage of the integrated design is its ability to identify an early possible tradeoff between process variables' tolerances and corresponding maintenance frequency, thus achieving an optimal solution on a concurrent basis in the design phase of new product/process development. As pointed out by Blanchard

[37], the "window of opportunity" in terms of design flexibility and life-cycle cost savings is much greater in the design phase than during the production phase.

Research on maintainability attempts to consider simultaneous maintenance and other design issues during the early design phase [36]. Many of the proposed approaches focused on improving the easiness and readiness of a constructed system's maintenance in the design phase by changing the system's mechanical structure or material selection [38], [39]. However, the tolerancing of process variables, one of the critical design aspects, was not considered in these treatments. The objective of this paper is to integrate preventive maintenance decision-making and process-oriented tolerancing in the design of multistation manufacturing processes. The product design information, such as product geometry and raw part tolerances, determined in the product design stage are assumed as known.

The proposed methodology in this paper is based on the state-space model of MMP [32], [33] and the tooling element degradation model [40], which offer the understanding of system response to variation inputs and system performance change over time, thus facilitating an integrated design procedure. Additionally, the presented work extends the process-oriented tolerancing method [28] by simultaneously considering both tolerance and maintenance policy as decision variables. The overall cost includes both the tolerance cost of tooling fabrication and maintenance cost. Loss of product quality is either considered as part of the overall cost function or treated as a constraint imposed on the optimization scheme, subject to the conditions of specific applications. This integrated design aims to minimize the overall long-run (life cycle) average cost of manufacturing systems.

This paper is organized in the following way. Section II presents the framework for the integrated tolerance and maintenance design. The cost structure and optimization scheme is formulated and interpreted. Section III studies the integrated design in the context of an automotive body assembly process. Optimality evaluation, numerical analysis, and cost comparisons are presented and elaborated. The paper is summarized in Section IV.

II. Framework for Optimal Design Through Integration of Tolerance Allocation and Maintenance Scheduling

This section presents basic concepts related to process-oriented tolerance allocation and maintenance scheduling, cost components, and optimization problem formulation, and an introduction to automotive body assembly processes.

A. Basic Concepts

Here, we introduce a set of concepts relevant to tolerance and maintenance design and discuss their meaning more specifically.

- ***Tooling elements and process variables:*** The tooling elements in a manufacturing process are used to locate, hold, cut, shape, or form the unfinished products. Examples of tooling elements include fixture elements used to locate and hold parts (locating pins in assembly processes) or tools needed to conduct fabrication operations (cutting tools in machining processes or a welding gun in joining processes). The functionality of each tooling element is described by process variables. In this paper, we consider an MMP consisting of n tooling elements that are distributed in N stations and described by the corresponding n process variables in vector $\mathbf{P} = [P_1 \, \ldots \, P_n]^T$.
- ***Key product characteristics (KPC) and product quality:*** KPC are critical product features whose deviations may significantly deteriorate the quality of a product. Their selection is based on product design requirements. KPC deviations, denoted as $\mathbf{Y} = [Y_1 \, \ldots \, Y_m]^T$, are used to define product quality, where m denotes the number of KPCs. In general, process variables, which represent the functionality of tooling elements, will impact product quality. In an MMP, the quality of a manufactured product at station k is affected by both the process variables at station k and the quality of the subassembly produced from the previous station, which is, in turn, affected by the process variables at station $k-1$. Therefore, the KPC deviations $\mathbf{Y}$ can be generally represented as a function of $\mathbf{P}$. The relationship between $\mathbf{P}$ and $\mathbf{Y}$ is illustrated in Segment I of Fig. 2.
- ***Static and dynamic imperfection of tooling elements:*** As mentioned earlier, a manufacturing system is inherently imperfect both statically and dynamically. These imperfections are characterized by the tolerance and functionality degradation of a tooling element, respectively. The degree of static imperfection of tooling elements is described by the tolerance of process variables, denoted as $\mathbf{T} = [T_1 \, T_2 \, \ldots \, T_n]^T$. Based on the definition of tolerance, $\mathbf{T}$ determines the initial varying ranges of process variables $\mathbf{P}$. The dynamic imperfection of a tooling element is caused by the degradation of its functionality over operation time, represented by the changes of process variables $\mathbf{P}$ over time. The functionality deterioration of tooling elements will, in turn, worsen product quality.
- ***Maintenance and process-oriented tolerancing:*** Process-oriented tolerancing and maintenance are used to address the static and dynamic imperfection of tooling elements, respectively. The study of maintenance actions in this paper is focused on replacements of tooling elements. For new tooling elements (without degradation), the allowable varying ranges of $\mathbf{P}$ are determined by their tolerances $\mathbf{T}$. Due to the continuous degradation of tooling elements during production time, $\mathbf{P}$ may shift continuously out of the ranges defined by initial tolerances $\mathbf{T}$. Maintenance action can restore the states of one or more tooling elements from their deteriorated states. In other words, by replacing the tooling element i with a new one, the maintenance action resets P_i to a value within its original range defined by T_i. An easy-to-adopt preventive maintenance policy is the age replacement policy, under which tooling element i is replaced when it reaches age a_i. Vector $\mathbf{a} \equiv [a_1 \, \ldots \, a_n]^T$ denotes the age replacement maintenance policies for all tooling elements. In discrete-part manufacturing processes, such as automotive body assembly processes, $\mathbf{a}$ is usually measured in terms

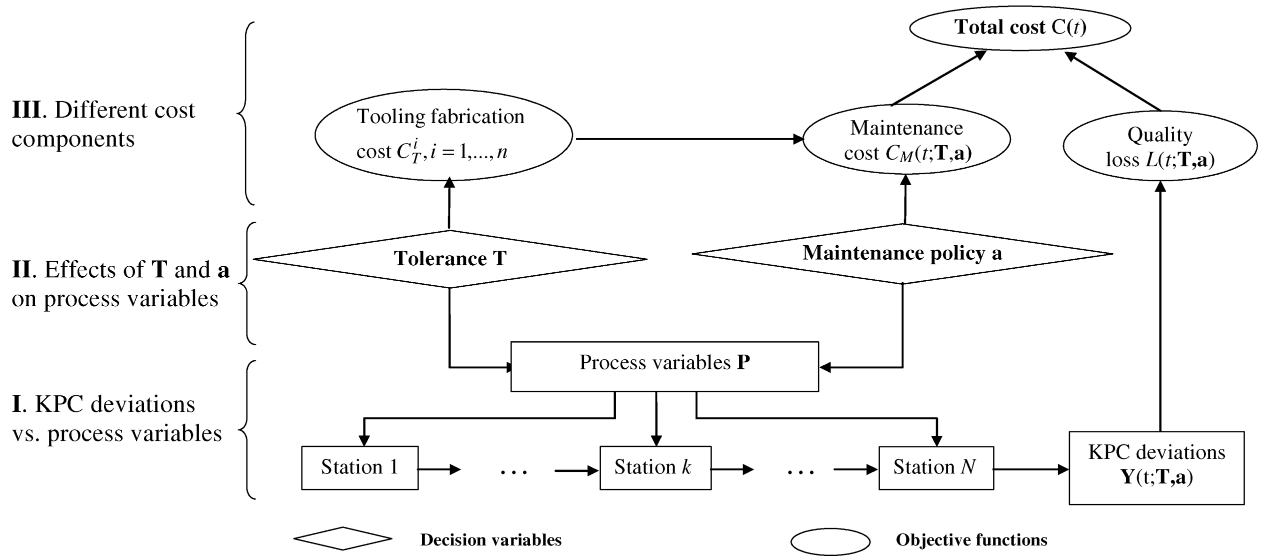

Fig. 2. Integration of tolerance and maintenance design in MMP.

of the number of fabrication operations performed by the manufacturing system.

$\mathbf{T}$ and $\mathbf{a}$ are both key decision variables in the integrated design of manufacturing systems. They determine the states of process variable $\mathbf{P}$ (i.e., the degree of functionality imperfection of tooling elements). The relationship of $\mathbf{T}$ and $\mathbf{a}$ to $\mathbf{P}$ is designated in Segment II of Fig. 2.

- ***Tooling fabrication cost, maintenance cost, and quality loss:***

  Costs are involved during the selection of tolerances and maintenance policies for manufacturing systems. The selection of tolerances affects the tooling fabrication cost, denoted by C_T^i for the ith tooling element $i = 1, \ldots, n$. The maintenance policy affects the maintenance cost at time t, denoted by $C_M(t)$. Here, time t, measured by the number of fabrication operations, is in a discrete scale. Additionally, loss is always incurred as product quality deteriorates. The cost due to product quality deterioration is indicated by a loss function $L(t)$ in this paper. These three cost components are shown in Segment III of Fig. 2 and will be discussed in detail in the following subsection.

B. Cost Components in the Integrated Design

This subsection will introduce various cost components related to process-oriented tolerancing, quality, and maintenance.

1) Tooling Fabrication Cost: Tooling fabrication cost is determined by the tolerance of process variables associated with the fabrication of a tooling element. Various cost functions of tolerances have been proposed for different tolerance allocation schemes [41]. There are two major types of tolerancing schemes: parametric and geometric [8]. Parametric tolerancing consists of identifying a set of parameters and assigning limits to the parameters that define a range of values. Geometric tolerancing assigns values to certain attributes of a feature, such as forms, orientations, runouts, and profiles. This paper uses the parametric tolerancing scheme to assign tolerance to process parameters/variables. As for parametric tolerancing, the reciprocal function and negative exponential function are most often used as the cost of tolerance. In this paper, the cost function for each tooling element is chosen to be a reciprocal function

$$C_T^i = \frac{w_i}{T_i}, \quad i = 1, \ldots, n \tag{1}$$

where T_i is the tolerance of the ith tooling element and w_i is the associated weighting coefficient. A tighter tolerance of a tooling element results in a higher tooling fabrication cost.

2) Maintenance Cost: In addition to the tooling fabrication cost, the maintenance cost of replacing tooling element i includes various other features including labor and basic repair facility costs. Apart from the tooling fabrication cost, the scheduled replacement is subject to another cost of c_{0i}^p (due to labor and management cost) for tooling element i. The replacement cost induced at time t can be written as

$$C_M(t) = \sum_{i \in J_t} \left(C_T^i + c_{0i}^p\right) = \sum_{i \in J_t} \left(\frac{w_i}{T_i} + c_{0i}^p\right) \tag{2}$$

where J_t is the index set of the tooling elements subject to a scheduled replacement at time t. If no tooling element is replaced at time t, $C_M(t)$ is zero. Obviously, J_t is affected by maintenance policy $\mathbf{a}$, and C_T^i is affected by tolerance $\mathbf{T}$. Thus, $C_M(t)$ depends on both $\mathbf{T}$ and $\mathbf{a}$. The notation $C_M(t; \mathbf{T}, \mathbf{a})$ is used when we need to explicate this dependency.

3) Quality Loss Function: Pignatiello [42] and Feng and Kusiak [43] extended Taguchi's quadratic loss function [44] for multidimensional variables. In this paper, the following quality loss function is used for multivariate variables:

$$L(\mathbf{Y}) = \mathbf{Y}^T \mathbf{S} \mathbf{Y} \tag{3}$$

where $\mathbf{S} = [s_{ij}]$ is a symmetric positive-definite matrix. From Fig. 2, the KPC deviation $\mathbf{Y}$ depends on tolerance $\mathbf{T}$, the maintenance policy $\mathbf{a}$, and the operation time t. Therefore, the quality loss function $L(\mathbf{Y})$ depends on all three variables. The dependency of L on t, $\mathbf{T}$, and $\mathbf{a}$ is explicated in the notation $L(t; \mathbf{T}, \mathbf{a})$.

C. Formulation of Optimization Problems

This subsection will formulate two optimization problems investigated in this paper.

1) Optimization Formulation With a Quality Loss Function: Under this scenario, the overall cost $C(t)$ includes both maintenance cost and quality loss and is

$$C(t) = C_M(t; \mathbf{T}, \mathbf{a}) + L(t; \mathbf{T}, \mathbf{a}).$$

Since time t is measured by the number of fabrication operations, the long-run expected production cost per unit time $\Phi(\mathbf{T}, \mathbf{a})$ can be written as

$$\Phi(\mathbf{T}, \mathbf{a}) \equiv \lim_{t\to\infty} \frac{\sum_{\tau=0}^{t} E(C(\tau))}{t} = \lim_{t\to\infty} \frac{\sum_{\tau=0}^{t} E(C_M(\tau; \mathbf{T}, \mathbf{a}) + L(\tau; \mathbf{T}, \mathbf{a}))}{t}. \quad (4)$$

The objective of the integrated tolerance and maintenance design is to minimize the long-run average production cost $\Phi(\mathbf{T}, \mathbf{a})$. The optimization problem is formulated as

$$\mathbf{F1}: \quad (\mathbf{T}^*, \mathbf{a}^*) = \operatorname{Arg}\min_{\mathbf{T},\mathbf{a}} (\Phi(\mathbf{T}, \mathbf{a})) \quad \text{subject to } T_i \geq 0 \text{ and } a_i \geq 0,\ \forall i. \quad (5)$$

Typically, a tight tolerance and high replacement frequency lead to high maintenance cost in the long run. On the other hand, loose tolerance and low replacement frequency lead to high quality loss. Hence, optimal designs of both tolerance and maintenance are needed to tradeoff the maintenance cost and quality loss.

2) Optimization Formulation With a Quality Constraint: If a quality loss function is difficult to determine in some manufacturing processes, the maximum acceptable variance of KPC deviations is generally used as the quality constraint. Therefore, an alternative is to formulate an optimization problem with a quality constraint: selecting the optimal tolerance and maintenance policy to minimize the maintenance cost, while satisfying the constraints on the KPC deviations at any operation time t. Since the time t is measured by the number of fabrication operations under this scenario, the long-run expected maintenance cost per unit time, denoted by $\Psi(\mathbf{T}, \mathbf{a})$, is

$$\Psi(\mathbf{T}, \mathbf{a}) \equiv \lim_{t\to\infty} \frac{\sum_{\tau=0}^{t} E(C_M(\tau))}{t}. \quad (6)$$

Then, the second formulation of the optimization problem is expressed as

$$\mathbf{F2}: \quad (\mathbf{T}^*, \mathbf{a}^*) = \operatorname{Arg}\min_{\mathbf{T},\mathbf{a}} \Psi(\mathbf{T}, \mathbf{a}) \quad \text{subject to } [\mathbf{K_Y}(t)]_{(i,i)} \leq h_i, \forall t, T_i \geq 0, a_i \geq 0,\ \forall i \quad (7)$$

where $\mathbf{K_Y}(t)$ is the predicted covariance matrix of the KPC deviation $\mathbf{Y}$ at time t; $[\mathbf{K_Y}(t)]_{(i,i)}$ is the $(i,i)^{\text{th}}$ entry of $\mathbf{K_Y}(t)$ (i.e., $[\mathbf{K_Y}(t)]_{(i,i)}$ is the variance of the ith KPC); and h_i is the threshold for the ith KPC variation. The threshold h_i is usually determined based on the specification of KPC deviation and the requirement on process capability indices, such as C_p and C_{pk}. This constraint requires that the variation of each KPC on the final product must be less than a given threshold, which is one of the commonly used criteria in the industry.

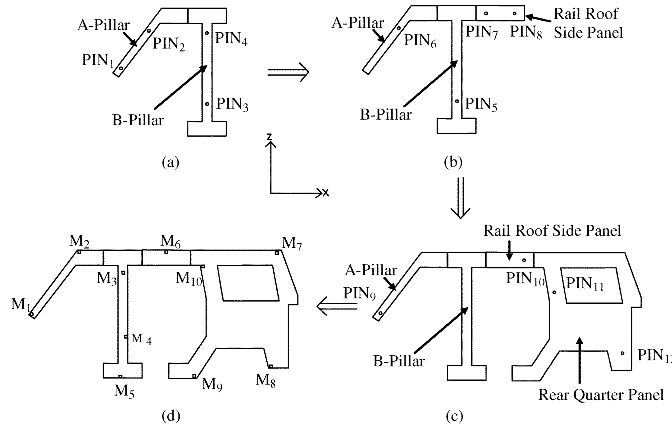

Fig. 3. Layout of the fixtures and the KPC points. (a) Station I; (b) Station II; (c) Station III; (d) Station IV: key product features.

The solution for the optimization problems formulated above depends on the model describing the impacts of $\mathbf{T}$ and $\mathbf{a}$ on the KPC deviation $\mathbf{Y}$. In this section, an explicit model for the relationship between $\mathbf{Y}$ and $(\mathbf{T}, \mathbf{a})$ cannot be seen. This model generally relies on the physical knowledge of specific manufacturing processes. In this paper, we will develop these necessary models in the context of automotive body assembly processes using the engineering knowledge of the process. The optimality of those two aforementioned optimization formulations ($\mathbf{F1}$ and $\mathbf{F2}$) will be discussed in the same process context as well. In the next subsection, we introduce some background on automotive body assembly processes, which is related to integrated tolerance and maintenance design.

D. Background of Automotive Body Assembly Processes

An automotive body is made up of more than 200 sheet metal parts through a process that involves about 80 assembly operations [40]. A side aperture inner-panel assembly shown in Fig. 3 is given as an example to illustrate a real automotive body assembly process. Here, four parts are assembled together at three stations. The A-Pillar and B-Pillar are assembled at station 1. The subassembly of A-Pillar and B-Pillar is assembled with the rail roof side panel at station 2. At station 3, the subassembly of A-Pillar, B-Pillar, and rail roof side panel is assembled with the rear quarter inner panel. The product quality is defined in terms of the deviations of ten KPC points measured at station 4 [Fig. 3(d)]. Four locating pins are used at each of the first three stations to position the parts/subassemblies. The assembly sequence of these four parts is illustrated in Fig. 4 and the layout of 12 locating pins used in this assembly is shown in Fig. 3(a)–(c).

As shown in Fig. 3(a)–(c) and Fig. 4, each part is located by a four-way locating pin and a two-way locating pin (the four-way and two-way pins are indicated in Fig. 4, such that the part movements are constrained within the part plane. The pin-hole locating pairs of a four-way locating pin and a two-way

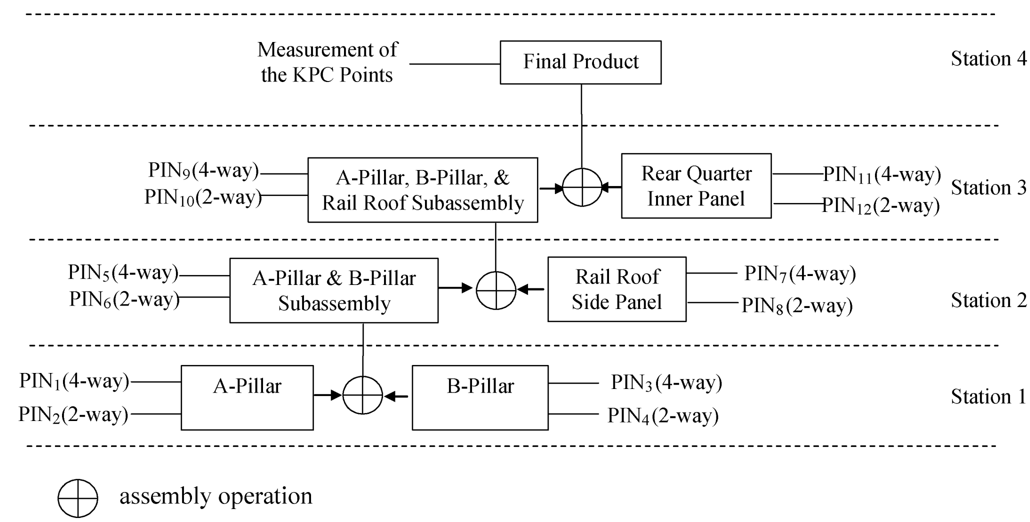

Fig. 4. Assembly sequences of the side aperture inner panel.

locating pin are shown in Fig. 5, where $d_{\rm pin}$ or $d_{\rm hole}$ is the diameter of a pin or hole, respectively, and P_i is the pin/hole clearance. A four-way hole is a round-shaped hole used to constrain the part movement in four directions. A two-way hole is a slot used to constrain the part movement in two directions. Since even a new locating pin has variations in its diameter, P_i is a random variable. The variation of P_i is determined by the design tolerance of locating pins. In this paper, we assume that $P_i \sim N(T_i/2, (T_i/6)^2)$. The objective of the integrated tolerance and maintenance design for the assembly process is to assign optimal tolerances and replacement cycles for each locating pin in order to minimize the overall production costs with desired product quality. In the next section, the variation propagation model as well as the effects of the tolerance $\mathbf{T}$ and the maintenance policy $\mathbf{a}$ on the product quality will be studied for a general N-station automotive body assembly process.

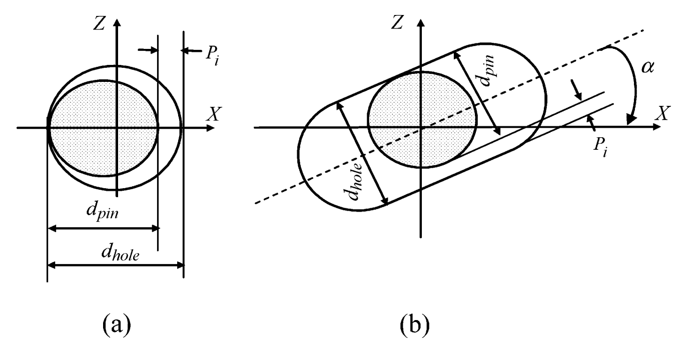

Fig. 5. Diagram of pin-hole locating pairs. (a) 4-way pin-hole; (b) 2-way pin-hole.

III. Integrated Design in Automotive Body Assembly Processes

The following are assumed from Section III-A to III-D for the automotive body assembly processes.

1) The variation propagation can be modeled by a linear state-space representation.
2) The tooling locating errors are independent of each other.
3) The degradation processes of different locating pins are independent.
4) Part deviations are considered only in a two-dimensional (2-D) plane (as in Fig. 5).

A. State-Space Modeling of Process Dimensional Variation Propagation

A state-space model has been developed in [32] and [33] to describe the variation propagation in a multistation assembly process as

$$\mathbf{X}(k) = \mathbf{A}(k-1)\mathbf{X}(k-1) + \mathbf{B}(k)\mathbf{U}(k) + \mathbf{W}(k) \quad (8)$$

$$\mathbf{Y}(k) = \mathbf{C}(k)\mathbf{X}(k) + \mathbf{V}(k) \quad (9)$$

where k is the station index, $k = 1, 2, \ldots, N$; N is the number of stations; $\mathbf{X}(k)$ is the part error vector at station k as defined in [32]; $\mathbf{U}(k)$ is the tooling locating error at station k, which is a random variable determined by the process variable $\mathbf{P}$ ($\mathbf{P}$ is the pin-hole clearances as shown in Fig. 5 for automotive body assembly processes); $\mathbf{Y}(k)$ is the KPC deviation vector of station k; and $\mathbf{W}(k)$ and $\mathbf{V}(k)$ are unmodeled process error and sensor noise. System matrices $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ encode process configuration, such as fixture layouts and sensor locations. A detailed expression regarding $\mathbf{A}, \mathbf{B}$, and $\mathbf{C}$ can be found in [33].

Usually product quality is defined in terms of variations of KPC points at the final station (i.e., station N). As such, we will express $\mathbf{Y}(N)$ in terms of tooling errors $\mathbf{U}(k)$. In this integrated design problem, sensor noise $\mathbf{V}(k)$ and unmodeled process error are not considered. The unmodeled process error $\mathbf{W}(k)$ results from the high-order terms in a Taylor expansion not included in the linear approximation shown in (8). A simulation study presented in [33] showed that the unmodeled process error $\mathbf{W}(k)$ can be neglected in a standard automotive body assembly process with 3-2-1 fixtures. Therefore, both $\mathbf{W}(k)$ and $\mathbf{V}(k)$ are neglected from the state-space model. From (8) and (9), an input–output relation can be obtained as

$$\mathbf{Y} \equiv \mathbf{Y}(N) = \Sigma_{k=1}^{N} \mathbf{C}(N)\mathbf{\Pi}(N,k)\mathbf{B}(k)\mathbf{U}(k) \quad (10)$$

where the state transition matrix $\mathbf{\Pi}(N,k)$ is defined as

$$\mathbf{\Pi}(N,k) = \mathbf{A}(N-1)\mathbf{A}(N-2)\cdots\mathbf{A}(k), \quad \text{and} \quad \mathbf{\Pi}(k,k) = \mathbf{I}, \quad N \geq k \geq 1. \quad (11)$$

Calculating variance/covariance for both sides of (10), we have

$$\mathbf{K_Y} = \Sigma_{k=1}^{N}\boldsymbol{\gamma}(k)\mathbf{K_U}(k)\boldsymbol{\gamma}^T(k) = \boldsymbol{\Gamma}\mathbf{K_U}\boldsymbol{\Gamma}^T \tag{12}$$

where $\mathbf{K_Y}$ and $\mathbf{K_U}(k)$ represent the covariance matrices of $\mathbf{Y}$ and $\mathbf{U}(k)$, respectively; $\boldsymbol{\gamma}(k) = \mathbf{C}(N)\boldsymbol{\Pi}(N,k)\mathbf{B}(k)$

$$\boldsymbol{\Gamma} = [\boldsymbol{\gamma}(1) \quad \ldots \quad \boldsymbol{\gamma}(N)],$$

$$\text{and} \quad \mathbf{K_U} = \begin{bmatrix} \mathbf{K_U}(1) & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \mathbf{K_U}(N) \end{bmatrix}.$$

B. Relationship Between Pin Tolerance and the Tooling Locating Error

The process variable P_i represents the actual clearance between the diameter of locating pin i and the nominal hole diameter as shown in Fig. 5. Although P_i is, in fact, bounded by $[0, T_i]$, it can be reasonably approximated through normal distribution $N(T_i/2, (T_i/6)^2)$. The tooling locating errors $\mathbf{U}(k)$, $k = 1, 2, \ldots, N$ are the deviations of the locating pins in both X and Z directions (the X and Z directions are shown in Fig. 5). Let $\mathbf{U} \equiv [\mathbf{U}(1) \ \ldots \ \mathbf{U}(N)]^T$ denote the tooling locating error at all stations in the automotive body assembly process, and U_i $i = 1, \ldots, n$ denote the ith element of $\mathbf{U}$. Hence, U_i is the deviation of locating pin i. The aggregated wear of a locating pin i at operation t, denoted by $\Delta_i(t)$, is expressed as

$$\Delta_i(t) = \Delta_i(t-1) + \Delta_{ri}(t) \tag{13}$$

where $\Delta_{ri}(t)$ is the incremental wear at operation t. According to [40], $\Delta_{ri}(t)$ is of lognormal distribution (i.e., $\Delta_{ri}(t) \sim \mathrm{LOGNORM}(\mu_{\Delta i}, \sigma_{\Delta i}^2)$). The relationship between the locating error (U_i) of locating pin i and the tolerance (T_i) and age (τ_i) of locating pin i has been derived in [28] as

$$E(U_i) = 0 \tag{14}$$

$$\mathrm{Var}(U_i) = \left(\frac{5}{18}\cdot\left(T_i + \frac{9}{5}\tau_i\cdot\mu_{\Delta i}\right)^2 + \tau_i\sigma_{\Delta i}^2 + \frac{\tau_i^2}{10}\cdot\mu_{\Delta i}^2\right) \tag{15}$$

where τ_i is the age of pin i. Since U_i depends on both T_i and τ_i, the notation $U_i(T_i, \tau_i)$ is used when we need to explicate this dependency. Please refer to Appendix A for the detailed derivation of (15).

C. Quality Loss Function of Automotive Body Assembly Processes

From (10) and (14), $E(\mathbf{Y}) = 0$. Furthermore, $\mathbf{K_U}(k)$ is diagonal based on Assumption 2 of Section III. By utilizing (12), the expected value of quality loss (defined in (3)) can be written as

$$\begin{aligned} E(L(\mathbf{Y})) &= E\left(\sum_{i=1}^{m}\sum_{j=1}^{m} s_{ij}Y_iY_j\right) \\ &= \sum_{i=1}^{m}\sum_{j=1}^{m} s_{ij}\mathrm{Cov}(Y_i, Y_j) \\ &= \sum_{i=1}^{n}\left([\boldsymbol{\Gamma}]_{(:,i)}^T\mathbf{S}[\boldsymbol{\Gamma}]_{(:,i)}\right)\mathrm{Var}(U_i) \\ &= \sum_{i=1}^{n}\rho_i\mathrm{Var}(U_i) \end{aligned} \tag{16}$$

where $\rho_i \equiv [\boldsymbol{\Gamma}]_{(:,i)}^T\mathbf{S}[\boldsymbol{\Gamma}]_{(:,i)}$ and s_{ij} is the (i,j)th element of matrix $\mathbf{S}$ used to define the quadratic quality loss.

D. Optimizations and Optimality

Two optimization formulations $\mathbf{F1}$ and $\mathbf{F2}$, one with a quality loss function and the other with a quality constraint function, will be further elaborated using process models of the automotive body assembly process. Since there are a number of locating pins in an automotive body assembly process, an efficient optimization procedure is required to achieve a feasible solution. Many nonlinear optimization algorithms can converge to a local optimum quickly. This subsection is focused on the study of optimality of the formulated optimization problems to guarantee that any local optimum is also a global optimum.

1) Optimality Analysis of Optimization Formulation F1: Optimization $\mathbf{F1}$ is formulated in (5) when quality loss function is considered as part of the objective function. Using the quality loss function in (16) for automotive body assembly processes, the objective function in (5) can be written as

$$\begin{aligned} \Phi(\mathbf{T}, \mathbf{a}) &= \lim_{t\to\infty}\frac{\sum_{\tau=0}^{t}\mathrm{E}\left(L(\mathbf{Y}(\tau)) + C_M(\tau)\right)}{t} \\ &= \lim_{t\to\infty}\frac{\sum_{\tau=0}^{t}\left(\sum_{i=1}^{n}\rho_i\mathrm{Var}(U_i) + \mathrm{E}\left(\sum_{i\in J_\tau}\left(\frac{w_i}{T_i} + c_{0i}^p\right)\right)\right)}{t} \\ &= \lim_{t\to\infty}\frac{\sum_{\tau=0}^{t}\left(\sum_{i=1}^{n}\left(L_i(\mathbf{Y}(\tau)) + \mathrm{E}\left(C_M^i(\tau)\right)\right)\right)}{t} \\ &= \sum_{i=1}^{n}\left(\lim_{t\to\infty}\frac{\sum_{\tau=0}^{t}\left(L_i(\mathbf{Y}(\tau)) + \mathrm{E}\left(C_M^i(\tau)\right)\right)}{t}\right) \end{aligned} \tag{17}$$

where $L_i(\mathbf{Y}(\tau)) \equiv \rho_i\mathrm{Var}(U_i)$, which denotes the contribution of pin i to the quality loss at time τ, and $C_M^i(\tau) \equiv \begin{cases}(w_i/T_i) + c_{0i}^p, & \text{if } i \in J_\tau \\ 0, & \text{otherwise}\end{cases}$ which is the replacement cost of pin i at time τ. From (15), $\mathrm{Var}(U_i)$ depends only on the age and tolerance of pin i. So both $C_M^i(\tau)$ and $L_i(\mathbf{Y}(\tau))$ are independent of replacement policies and tolerances of other locating pins. Based on (17) and assumption 3 in Section III, the optimization problem of the whole fixture system defined in (5) can be decomposed into optimization problems for each single locating pin as follows:

$$(T_i^*, a_i^*) = \mathrm{Arg}\min_{T_i, a_i}\left(\Phi_i(T_i, a_i)\right)$$
$$\text{subject to } T_i \geq 0 \text{ and } a_i \geq 0,\ \forall i \tag{18}$$

where $\Phi_i(T_i, a_i) \equiv \lim_{t\to\infty}\sum_{\tau=0}^{t}(L_i(\mathbf{Y}(\tau)) + E(C_M^i(\tau)))/t$.

Since each replacement cycle for locating pin i is fixed as a_i, we see that

$$\begin{aligned} \Phi_i(T_i, a_i) &= \frac{\text{average cost per replacement cycle for pin } i}{\text{replacement cycle of pin } i}, \\ &\approx \frac{\int_0^{a_i}\rho_i\mathrm{Var}(U_i)dt + \frac{w_i}{T_i} + c_{0i}^p}{a_i} \end{aligned} \tag{19}$$

where $\mathrm{Var}(U_i)$ is calculated by (15). Here, instead of a summation, the integral is used to approximate the cumulative quality

TABLE I
NOMINAL X-Z COORDINATES FOR LOCATING POINTS

Locating Points		P_1&P_9	P_2&P_6	P_3&P_5	P_4	P_7	P_8&P_{10}	P_{11}	P_{12}
Nominal Coordinates (mm)	x	367.7	667.5	1272.7	1301.0	1470.7	1770.5	2120.3	3026.3
	z	906.1	1295.4	537.4	1368.9	1640.4	1702.6	1402.8	950.3

TABLE II
NOMINAL X-Z COORDINATES FOR KPC POINTS

KPC Points		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
Nominal Coordinates (mm)	x	271.5	565	1289	1306	1244	1640	2884	2743	1838	1980
	z	905.0	1634	1227	633	85	1781	1951	475	226	1459

TABLE III
PARAMETERS USED IN THE SIMULATION

μ_Δ (mm)	σ_Δ (mm)	$c_0 \equiv c_{0i}^p$ (\$)	w_i (\$·mm)	q (\$/mm^2)
5×10^{-7}	5×10^{-5}	200	200	1

loss until time a_i. This approximation is reasonable due to the fact that there are numerous operations that occur on any given operating day for manufacturing systems, such as an automotive body assembly process. In addition, the tooling replacement cycle typically ranges from several weeks to months. Because the replacement cycle a_i generally contains a large number of operations, the integral is a good representation of the summation of the quality loss. In the latter discussion, (19) will be considered as the exact long-run average production cost $\Phi_i(T_i, a_i)$ for pin i.

Substituting (15) into (19) gives us

$$\Phi_i(T_i,a_i) = \rho_i\left(\frac{5}{18}\left(T_i+\frac{9}{10}\mu_{\Delta i}a_i\right)^2 + \frac{13}{120}\mu_{\Delta i}^2a_i^2+\frac{1}{2}\sigma_{\Delta i}^2a_i\right)+\frac{w_i}{T_ia_i}+\frac{c_{0i}^p}{a_i}.$$

Given $T_i > 0$ and $a_i > 0$, $\nabla^2(1/T_ia_i) = \begin{pmatrix} 2/T_i^3a_i & 1/a_i^2T_i^2 \\ 1/a_i^2T_i^2 & 2/a_i^3T_i \end{pmatrix}$ is positive definite, implying that $1/T_ia_i$ is a convex function of T_i and a_i. Also, ρ_i,κ_i,μ_i, σ_i, w_i, c_{0i}^p, $\forall i$ are non-negative. It is easy to see that $\Phi_i(T_i, a_i)$, which is a linear combination of several convex functions with non-negative coefficients, is also a convex function of a_i and T_i. Thus, the optimality analysis for the optimal solution of (18) can be stated as follows.

Result 1: The objective function $\Phi_i(a_i, T_i)$ in (18) is a convex function and, hence, the optimization problem described by (18) converges to a global optimum.

Optimality Analysis of Optimization Formulation F2: Equation (7) is used for the optimization formulation $\mathbf{F2}$ when product quality is treated as the constraint. By removing $L(\mathbf{Y})$ from the objective function and then following the derivation of (17)–(19) in Section III-D1, we can express the long-run average maintenance cost as

$$\Psi(\mathbf{T},\mathbf{a}) = \sum_{i=1}^{n}\frac{\frac{w_i}{T_i}+c_{0i}^p}{a_i}.$$

The following lemmas are used to show that the local minimum is also the global minimum under this formulation.

Lemma 1: The cost function $\Psi(\mathbf{T},\mathbf{a})$ is a convex function.

For $T_i > 0$ and $a_i > 0$, $1/T_ia_i$ is a convex function; for all i, $1/a_i$ is a convex function; and w_i and c_{0i}^p are non-negative. Thus, $\Psi(\mathbf{T},\mathbf{a})$, which is a linear combination of convex functions, is also a convex function.

Lemma 2: The constraint of $\mathbf{F2}$ is a convex set.

Proof: Please refer to Appendix B for the proof.

Result 2: The nonlinear optimization problem (NLP) stated in (7) converges to a global minimum $\mathbf{T}^*$ and $\mathbf{a}^*$ for the automotive body assembly processes.

Proof: Based on Lemma 2, the constraint in (7) is a convex set. From Lemma 1, the objective function of (7) is a convex function. Thus, every local minimum of the objective function is a global minimum within the constraint [46].

E. Numerical Analysis

Numerical analysis is conducted for the assembly process of the side aperture inner-panel as shown in Fig. 3. Coordinates of locating points and KPC points, and other parameters used in this study are listed in Tables I–III, respectively. The KPC deviation of this side aperture inner-panel subassembly process affects the difficulty of panel fitting in downstream stations. Since each selected KPC deviation has a similar effect on panel fitting, they are assumed to have independent and equal contributions on product quality loss. That is, $\mathbf{S} = q\mathbf{I}$, where $\mathbf{I}$ is an identity matrix and q is the weight for all KPCs.

1) Optimal Tolerance and Maintenance Design for Optimization Formulation F1: Using the parameters in Tables I–III, the optimal tolerance and replacement cycle for each locating pin are listed in Table IV. The difference in the optimal assignments of tolerance and replacement cycle for different pins is caused by the fact that the contribution of each locating pin on quality loss is different and determined by its type (four way or two way) and geometrical position. If a locating pin has little contribution to quality loss, then a loose tolerance and a long replacement cycle will be assigned to it. This helps to reduce maintenance cost while keeping quality loss at an acceptable level.

The optimization problem is solved by using the MATLAB function *fmincon* which utilizes a sequential quadratic programming (SQP) method [47]. SQP methods have the property of

TABLE IV
OPTIMAL TOLERANCE AND REPLACEMENT CYCLE OF OPTIMIZATION FORMULATION **F1**

i	1	2	3	4	5	6
T_i(mm)	0.078	0.105	0.083	0.100	0.086	0.102
a_i($\times 10^5$ operations)	1.48	2.06	1.60	1.94	1.65	1.99
i	7	8	9	10	11	12
T_i(mm)	0.112	0.093	0.078	0.086	0.072	0.079
a_i($\times 10^5$ operations)	2.20	1.79	1.49	1.65	1.35	1.50

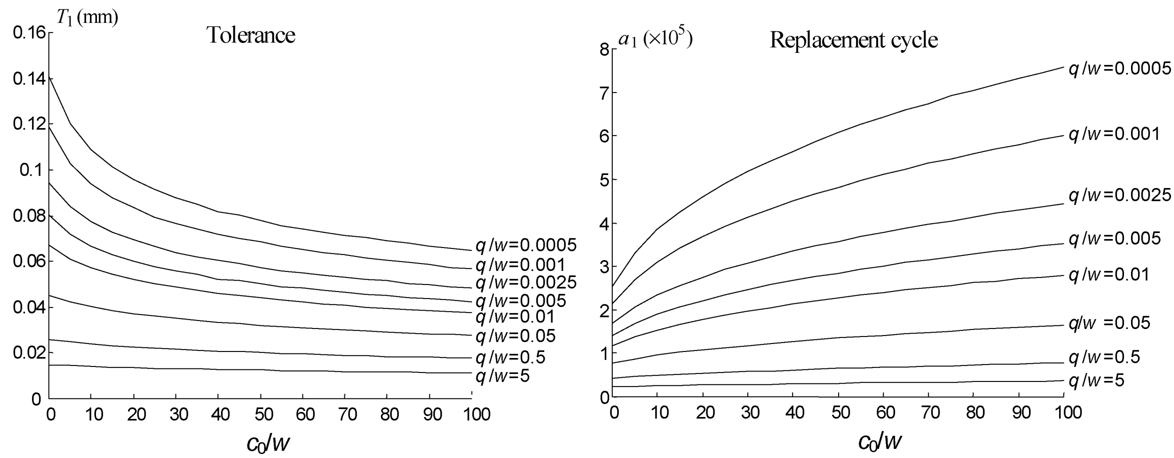

Fig. 6. Optimal tolerance and maintenance schedule for different combinations of cost ratios.

TABLE V
OPTIMAL TOLERANCE AND REPLACEMENT CYCLES OF OPTIMATION FORMULATION **F2**

i	1	2	3	4	5	6
T_i(mm)	0.109	0.172	0.100	0.144	0.137	0.176
a_i($\times 10^5$ operations)	1.24	2.10	1.14	1.70	1.61	2.14
i	7	8	9	10	11	12
T_i(mm)	0.288	0.148	0.163	0.153	0.159	0.152
a_i($\times 10^5$ operations)	3.87	1.76	1.97	1.82	1.91	1.81

fast convergence on a local optimum. As a result, it is important to understand the relationship between the local optimum and global optimum, which is the major focus of Section III-D. From Section III-D, we know that the nonlinear optimization problem will converge to a global optimum. For the assembly process shown in Fig. 3, it takes MATLAB 0.98 s to converge to the local minimum (also guaranteed to be global minimum based on the optimality study) for optimization formulation I and 6.7 s for optimization formulation II on a Pentium III 1.2-GHz PC. The running time is expected to be shorter if the program is coded in C or FORTRAN.

In addition, the optimal solution is sensitive to the cost ratios q/w and c_0/w. The optimal tolerance and replacement cycle of locating pin P_1 with different combinations of q/w and c_0/w are shown in Fig. 6. Similar plots can be easily obtained for other locating pins. Fig. 6 can be used as a guideline for the optimal selection of pin tolerance and maintenance schedule for various applications with specific cost ratios. From Fig. 6, the optimal tolerance T_1 decreases when the cost ratio c_0/w or q/w increases. That is, a tighter tolerance is used when the fixed maintenance cost (modeled by c_0) and/or the quality loss (modeled by q) becomes significant compared with the tooling fabrication cost (modeled by w). On the other hand, the optimal replacement cycle a_1 rises with the increase of c_0/w or decrease of q/w. That is, a longer replacement cycle is used when the fixed maintenance cost becomes significant and/or the quality loss becomes less significant when compared with the tooling fabrication cost.

2) Optimal Tolerance and Maintenance Design for Optimization Formulation F2: For this example, we require that the maximal 6σ of the KPC deviations should not exceed 1.50 mm, which is an appropriate specification for KPC deviations of a subassembly of an automotive body. This specification corresponds to a C_p value equal to 1. Under the scenario of optimization formulation **F2**, we find the optimal tolerance assignment and tooling replacement cycle, which are shown in Table V. Since product quality is treated as a constraint, the optimal solution depends only on the cost ratio c_0/w. The optimal tolerance assignment and maintenance schedule under a different cost ratio c_0/w for locating pin P_1 are illustrated in Fig. 7. It can be seen from Fig. 7 that the optimal tolerance decreases over c_0/w while the optimal replacement cycle increases over c_0/w. The results are consistent with those in Fig. 6. The same intuitive interpretation can be applied here.

3) Cost Comparison Under Different Design Schemes: Ding *et al.* [28] proposed an optimal tolerance design scheme with consideration of the relationship between process variables and product quality. However, the maintenance schedule in [28] is set as a fixed replacement cycle of 0.6×10^5 operations for each locating pin purely

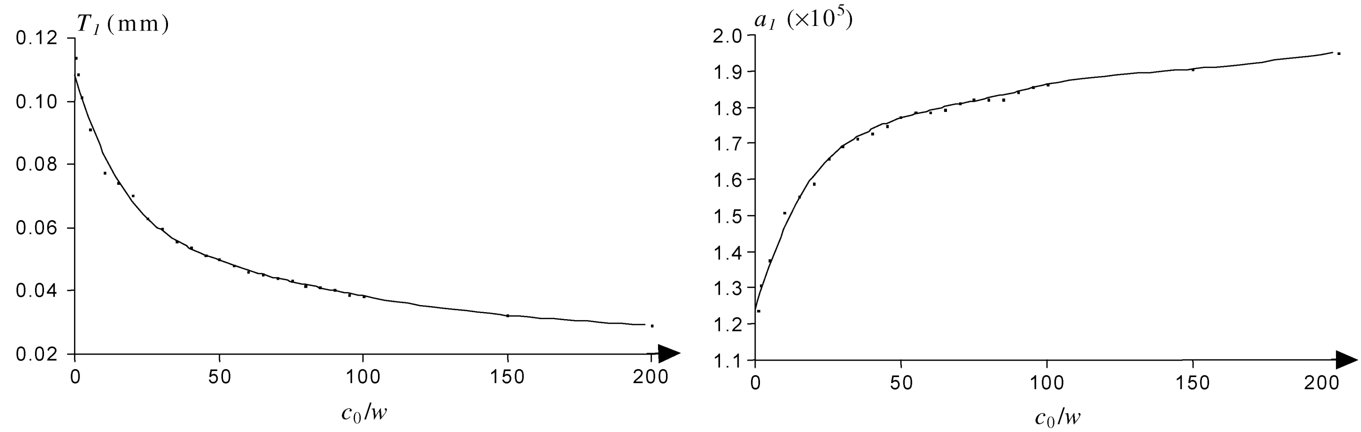

Fig. 7. Optimal tolerance assignment and maintenance schedule under different c_0/w.

TABLE VI
OPTIMAL TOLERANCE ASSIGNMENT WITH FIXED REPLACEMENT CYCLE OF 0.6×10^5 OPERATIONS (in millimeters)

T_1	T_2	T_3	T_4	T_5	T_6
0.17	0.31	0.15	0.25	0.23	0.33
T_7	T_8	T_9	T_{10}	T_{11}	T_{12}
0.59	0.26	0.30	0.27	0.28	0.26

TABLE VII
COMPARISON OF PRODUCTION COST FOR OPTIMIZATION FORMULATION **F1**

Scenario	**Formula**	**Uniform 0.25 mm Tolerance**	**Fixed 0.6×10^5 Replacement Cycle**	**Integration of Tolerance and Maintenance**
Tooling Fabrication Cost at the First Setup($)	$\sum_{i=1}^{n} \frac{w_i}{T_i}$	9.6×10^3	9.41×10^3	27.4×10^3
Long-Run Average Tooling Fabrication Cost ($/operation)	$\lim_{t\to\infty} \frac{\sum_{\tau=0}^{t} E\left(\sum_{i\in J_\tau} \frac{w_i}{T_i}\right)}{t}$	0.160	0.157	0.165
Long-Run Average Maintenance Cost ($/operation)	$\lim_{t\to\infty} \frac{\sum_{\tau=0}^{t} E(C_M(\tau;\mathbf{T},\mathbf{a}))}{t}$	0.200	0.197	0.179
Long-Run Average Quality Loss ($/operation)	$\lim_{t\to\infty} \frac{\sum_{\tau=0}^{t} E(L(t;\mathbf{T},\mathbf{a}))}{t}$	0.484	0.555	0.175
Long-Run Overall Production Cost ($/operation)	$\lim_{t\to\infty} \frac{\sum_{\tau=0}^{t} E(C_M(\tau;\mathbf{T},\mathbf{a})+L(t;\mathbf{T},\mathbf{a}))}{t}$	0.684	0.752	0.354

based on experience. For the purpose of comparison, the tolerance assignment based on the methods proposed in [28] is presented in Table VI. The design proposed in [28] yields a looser tolerance and shorter replacement cycle than the optimal integrated design of this paper, using either optimization formulation **F1** or **F2**. Ding *et al.* [28] compared their design with the tolerance assignment scheme of uniform 0.25-mm tolerance for each locating pin. Here, the cost efficiencies of the two design schemes used in [28] are compared in Table VII with the optimal integrated design using **F1**.

From Table VII, one can see that although our integrated tolerance and maintenance design suffers a higher tooling fabrication cost at the first setup due to its tighter tolerance, it has a similar long-run average tooling fabrication cost to the other two design schemes due to its lower replacement frequency (second row in Table VII). More important, the tighter tolerance and lower replacement frequency lead to a much lower long-run average maintenance cost and quality loss than the other two designs. Therefore, in terms of the overall production cost, including long-run maintenance cost and quality loss, the integrated tolerance and maintenance design is much better when compared with the other two design schemes.

The cumulative total production costs over operation time for these three design schemes are compared in Fig. 8. It confirms that the integrated design faces a higher initial setup cost than the other two designs. However, after $\tau_0 (\approx 0.3 \times 10^5)$ cycles of operations, the process under the integrated design scheme becomes increasingly more cost efficient. The optimal integrated design, although obtained using infinite-horizon long-run average cost criteria, can lead to significant cost savings if the con-

TABLE VIII
COMPARISON OF MAINTENANCE COST AND QUALITY FOR OPTIMIZATION FORMULATION **F2**

Scenario	Uniform 0.25 mm Tolerance	Fixed 0.6×10^5 Replacement Cycle	Integration of Tolerance and Maintenance
Long Run Maintenance Cost ($/operation)	0.20	0.20	0.11
Maximum 6σ of KPCs (mm)	1.76	1.50	1.50

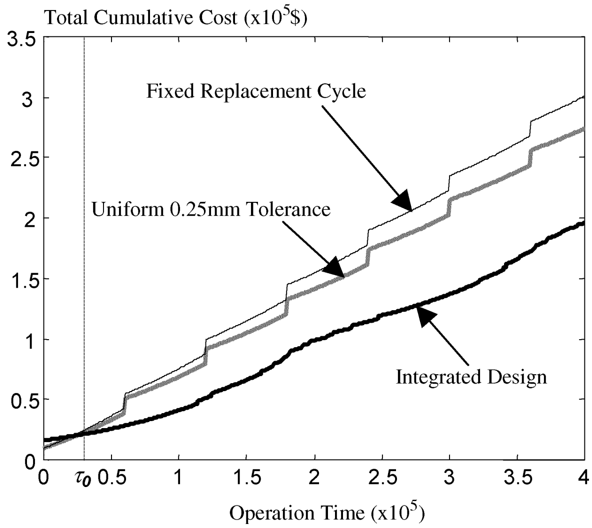

Fig. 8. Cumulative costs at different operation time for three design schemes.

cerned time horizon is greater than $2\tau_0(0.6 \times 10^5 \text{ cycles})$. However, if the time horizon is less than $2\tau_0$, the infinite-horizon cost criteria may not be appropriate to approximate the finite horizon reality of the application.

As for the optimization problem with a quality constraint, both [28] and the integrated design using formulation **F2** in this paper impose a constraint that the maximal 6σ of the KPC deviations cannot exceed 1.50 mm. Table VIII shows that the long-run maintenance cost using the integrated design methodology is 45% lower than that of the other two design schemes. It should be noted that the costs in Table VIII are average costs per unit operation. Typical daily throughputs of an automotive body assembly process range from 500–1500 products. Therefore, 500–1500 assembly operations need to be performed each day by the system, which corresponds to a yearly savings of tens of thousands of dollars if the integrated design is used. In addition, the four-station side aperture inner-panel assembly process studied in this example is just a small portion of the automotive body assembly process. A typical automotive body assembly process consists of 60–100 assembly stations [48]. Much larger savings are therefore expected if the integrated design methodology is applied for the entire automotive body assembly process. The design scheme proposed by [28] is better than the uniform tolerancing scheme since it has the same maintenance cost but smaller 6σ. With the same 6σ, the integrated design has a much lower maintenance cost than the design scheme proposed by [28]. Thus, it can be concluded that the integrated tolerance and maintenance design proposed in this paper are more sophisticated and can achieve much better performance than the other design schemes in various optimization settings.

IV. SUMMARY

A general framework of integrating two traditionally separated methodologies—tolerance allocation and maintenance scheduling—has been presented in this paper. This integrated design methodology simultaneously addresses both static and dynamic imperfection of system performance of MMPs, aiming to achieve the optimal system performance with minimum overall production cost. Recent research on modeling and analysis of MMPs has significantly enhanced the current understanding of the process and serves as the basis for the development of the integrated framework of tolerance and maintenance design. In addition to these basic process models, two nonlinear optimization problems are formulated by treating the quality criterion as either a part of the cost function or the constraint function, respectively. The optimality of both formulations has been studied in the generic scenario of automotive body assembly processes. When compared with other separated designs, the integrated design methodology, using either optimization formulation, leads to more desirable system performance with a significant reduction in production cost.

In this paper, the automotive body assembly process with rigid parts is used as an example to demonstrate the proposed methodology. It is worthwhile to note that the overall integrated framework, the state-space model for variation propagation, and the tooling degradation model are fairly general for various types of MMPs. For example, the state-space model in Section III-A has been applied in assembly processes with compliant parts [49] and transfer line machining processes [50]–[52]. When extending the methodology developed in this paper to some other MMP, additional research is essential in order to study the relationship between tolerance and tooling error, as in Section III-B of this paper. For assembly processes using locating pins as locators, the pin-hole relationship studied in Section III-B can still be applied. For other processes, such as machining, further investigation on tolerance-error relationship is needed for tools, such as milling cutters and drills. With enhanced understanding of tooling performance and its relationship with product quality in specific processes, the proposed framework and methodology to integrate tolerance and maintenance design can be applied toward other manufacturing systems.

APPENDIX A
PROOF OF (15)

We need to show

$$\mathrm{Var}(U_i) = \left(\frac{5}{18} \cdot \left(T_i + \frac{9}{5}\tau_i \cdot \mu_{\Delta i} \right)^2 + \tau_i \cdot \sigma_{\Delta i}^2 + \frac{\tau_i^2}{10} \cdot \mu_{\Delta i}^2 \right)$$

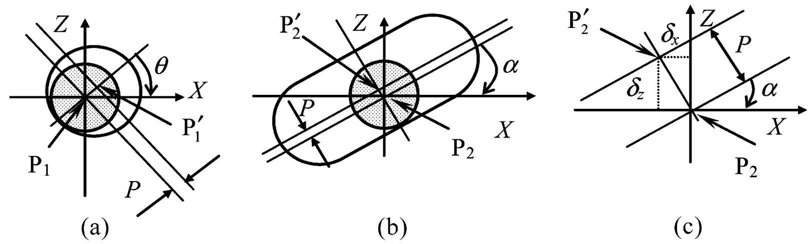

Fig. 9. Clearance-induced deviation.

which is (15). Since U_i, the tooling locating error, is the deviation of the locating pin i, we should study the deviation of locating pins first. The deviation of a four-way locating pair is exemplified in Fig. 9a, in which the deviations of point P_1' (the center of the hole) from point P_1 (the center of the pin) in both X and Z directions are

$$\Delta X = P\cos\theta \tag{A.1}$$

$$\Delta Z = P\sin\theta \tag{A.2}$$

where P is the distance between P_1' and P_1, and θ is the contact orientation. P is assumed as following normal distribution $N(T_i/2, (T_i/6)^2)$ as in Section III. The clearance of a four-way locating pair is considered as homogenous in all directions and, thus, the orientation angle θ is of the uniform distribution between 0 and 2π (i.e., $\theta \sim \mathrm{U}(0, 2\pi)$). Given that the two random variables δ and θ are independent of each other, the statistics regarding $\varDelta X$ and $\varDelta Z$ are shown as follows:

$$\begin{aligned}\mathrm{E}(\Delta X) &= \mathrm{E}(P\cos\theta)\\ &= \mathrm{E}(P)\cdot\mathrm{E}(\cos\theta) = 0,\end{aligned} \tag{A.3}$$

$$\begin{aligned}\mathrm{E}(\Delta Z) &= \mathrm{E}(P\sin\theta)\\ &= \mathrm{E}(P)\cdot\mathrm{E}(\sin\theta) = 0,\end{aligned} \tag{A.4}$$

$$\begin{aligned}\sigma^2_{X,4-\mathrm{way}} &= \mathrm{E}(\Delta X^2)\\ &= \mathrm{E}(P^2)\cdot\mathrm{E}(\cos^2\theta) = \frac{5T^2}{36}\end{aligned} \tag{A.5}$$

$$\begin{aligned}\sigma^2_{Z,4-\mathrm{way}} &= \mathrm{E}(\Delta Z^2)\\ &= \mathrm{E}(P^2)\cdot\mathrm{E}(\sin^2\theta) = \frac{5T^2}{36}\end{aligned} \tag{A.6}$$

$$\begin{aligned}\mathrm{Cov}(\Delta X, \Delta Z) &= \mathrm{E}(\Delta X\Delta Z) = \mathrm{E}(P^2\sin\theta\cos\theta)\\ &= \mathrm{E}(P^2)\cdot\mathrm{E}(\sin\theta\cos\theta) = 0\end{aligned} \tag{A.7}$$

where $\mathrm{E}(\cdot)$ is the expectation and $\mathrm{Cov}(\cdot,\cdot)$ represents covariance of two random variables. These equations imply that deviations of a four-way locating pin in both directions have zero mean and the same variances and they are also uncorrelated.

The geometrical relationship of a two-way locating pair with orientation angle α shown in Fig. 9(b) and (c) reads

$$\delta_X = P\sin\alpha\cdot\kappa \quad \text{and} \quad \delta_Z = -P\cos\alpha\cdot\kappa \tag{A.8}$$

where P is defined in the same way as before and κ is a binary random variable equal to either 1 or -1. It can be seen that if the pin touches the top (or left if α approaches 90°) edge of pin-hole, then κ is 1; if the pin touches the bottom (or right if α approaches 90°) edge of pin-hole, then κ is -1. Also, κ is independent of P. Hence, the deviation associated with a two-way locating pair can then be expressed as

$$\mathrm{E}(\delta_{\mathrm{X}})\mathrm{E}(\delta_{\mathrm{Z}}) = 0, \tag{A.9}$$

$$\begin{aligned}\sigma^2_{X,2-\mathrm{way}} &= \mathrm{E}(P^2\sin^2\alpha\cdot\kappa^2)\\ &= \frac{5T^2}{18}\cdot\sin^2\alpha,\end{aligned} \tag{A.10}$$

$$\begin{aligned}\sigma^2_{Z,2-\mathrm{way}} &= \mathrm{E}(P^2\cos^2\alpha\cdot\kappa^2)\\ &= \frac{5T^2}{18}\cdot\cos^2\alpha,\end{aligned} \tag{A.11}$$

$$\begin{aligned}Cov(\delta_X, \delta_Z) &= \mathrm{E}(P^2\cos\alpha\sin\alpha\cdot\kappa^2)\\ &= \frac{5T^2}{18}\cos\alpha\sin\alpha.\end{aligned} \tag{A.12}$$

A stochastic degradation model of a locating pin has been given in (13). The change of clearance of the pin-hole locating pair can be computed by

$$d(\tau) = P + \Delta(\tau) \tag{A.13}$$

where $d(\tau)$ is the pin-hole clearance at age τ of the locating pin and P is the initial clearance which is the same as that in (A.1) and (A.2). In the following derivations, we assume that the initial clearance P, orientation variables θ and κ, and aggregated wear $\varDelta_i(\tau)$ are independent of each other. Based on these properties and assumptions, the following relationships can be obtained by substituting (A.13) into (A.5), (A.6), (A.10), and (A.11), respectively

$$\begin{aligned}\sigma^2_{X,4-\mathrm{way}}(\tau) &= \mathrm{E}\left((P+\varDelta(\tau))^2\cdot\cos^2\theta\right)\\ &= \frac{1}{2}\mathrm{E}\left((P+\varDelta(\tau))^2\right)\end{aligned} \tag{A.14}$$

$$\begin{aligned}\sigma^2_{Z,4-\mathrm{way}}(\tau) &= \mathrm{E}\left((P+\varDelta(\tau))^2\cdot\sin^2\theta\right)\\ &= \frac{1}{2}\mathrm{E}\left((P+\varDelta(\tau))^2\right)\end{aligned} \tag{A.15}$$

$$\begin{aligned}\sigma^2_{X,2-\mathrm{way}}(\tau) &= \mathrm{E}\left((P+\Delta(\tau))^2\sin^2\alpha\cdot\kappa^2\right)\\ &= \sin^2\alpha\cdot\mathrm{E}\left((P+\Delta(\tau))^2\right)\end{aligned} \tag{A.16}$$

$$\begin{aligned}\sigma^2_{Z,2-\mathrm{way}}(\tau) &= \mathrm{E}\left((P+\Delta(\tau))^2\cos^2\alpha\cdot\kappa^2\right)\\ &= \cos^2\alpha\cdot\mathrm{E}\left((P+\Delta(\tau))^2\right)\end{aligned} \tag{A.17}$$

where

$$\begin{aligned}&\mathrm{E}\left((P+\Delta(\tau))^2\right)\\ &\quad= \mathrm{E}\left(P^2 + 2P\Delta(\tau) + \Delta^2(\tau)\right)\\ &\quad= \mathrm{E}(P^2) + 2\cdot\mathrm{E}(P)\cdot\mu_\Delta\tau\\ &\qquad+ \mathrm{Var}\left(\Delta(\tau)\right) + (\mu_\Delta\tau)^2\\ &\quad= \frac{5T^2}{18} + T\cdot\mu_\Delta\tau + \tau\cdot\sigma^2_\Delta + (\mu_\Delta\tau)^2\\ &\quad= \frac{5}{18}\cdot\left(T + \frac{9}{5}\mu_\Delta\tau\right)^2 + \tau\cdot\sigma^2_\Delta + \frac{1}{10}\cdot(\mu_\Delta\tau)^2\end{aligned} \tag{A.18}$$

Since U_i is the deviation of the center of locating pin i, which includes deviations in both X-direction and Z-direction, by adding deviations in X-direction and Z-direction, it can be seen from (A.14)–(A.18) that $\mathrm{Var}(U_i) = (5/18\cdot(T_i+(9/5)\tau_i\cdot\mu_{\Delta i})^2+\tau_i\sigma_{\Delta i}^2+(\tau_i^2/10)\cdot\mu_{\Delta i}^2)$ for each locating pin i, which proves (15).

APPENDIX B
PROOF OF LEMMA 2

From (12), $[\mathbf{K_Y}(t)]_{(i,i)}$ is a linear combination of $\mathrm{Var}(U_i)$, $i = 1, 2, \ldots, 2n$ with non-negative coefficients. It is known that given tolerance $\mathbf{T}$ and maintenance policy $\mathbf{a}$, $\mathbf{K_Y}(t)$ depends on the age of each locating pin τ_i,$i = 1, 2, \ldots, n$. This dependency is explicated with the notation $\mathbf{K_Y}(t)|_{\tau_1,\ldots,\tau_n}$. From (15), we can see that $\mathrm{Var}(U_i)$ is increasing over $\tau_{\lceil i/2\rceil}$. This monotonic property implies that $[\mathbf{K_Y}(t)]_{(i,i)}$ achieves its maximum at the time when the age of each locating pin is equal to its scheduled replacement cycle. That is

$$\max_{\tau_1,\ldots,\tau_n} [\mathbf{K_Y}(t)]_{(i,i)} = [\mathbf{K_Y}(t)]_{(i,i)}\Big|_{\tau_1=a_1,\ldots,\tau_n=a_n}.$$

As such, the constraint of $\mathbf{F2}$ can be written as

$$\begin{aligned}&\left\{\mathbf{T},\mathbf{a}\big|\,[\mathbf{K_Y}(t)]_{(i,i)} \le h_i, \forall t, T_i \ge 0, a_i \ge 0, \forall i\right\}\\&\quad=\left\{\mathbf{T},\mathbf{a}\left|[\mathbf{K_Y}(t)]_{(i,i)}\right|_{\tau_1=a_1,\ldots,\tau_n=a_n}\right.\\&\qquad\left.\le h_i, T_i \ge 0, a_i \ge 0, \forall i\right\}. \qquad\qquad (A.19)\end{aligned}$$

From (15), $\mathrm{Var}(U_i(T_{\lceil i/2\rceil}, a_{\lceil i/2\rceil}))$ is a convex function of $\mathbf{T}$ and $\mathbf{a}$. So $[\mathbf{K_Y}(t)]_{(i,i)}|_{\tau_1=a_1,\ldots\tau_n=a_n}$ is a convex function of $\mathbf{T}$ and $\mathbf{a}$, $\forall i$. Then, the set $\{\mathbf{T},\mathbf{a}|[\mathbf{K_Y}(t)]_{(i,i)}|_{\tau_1=a_1,\ldots,\tau_n=a_n} \le h_i, T_i \ge 0, a_i \ge 0, \forall i\}$ is convex. Equation (A.19) further leads us to the conclusion that the constraint set of $\mathbf{F2}$ is convex. □

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