CIRP Annals - Manufacturing Technology 64 (2015) 149–152

Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: http://ees.elsevier.com/cirp/default.asp

Hierarchical synthesis of multi-level design parameters in assembly system

Pasquale Franciosa, Dariusz Ceglarek (1)*

Digital Lifecycle Management (DLM), WMG, University of Warwick, Coventry CV4 7AL, United Kingdom

ARTICLE INFO

Keywords:
Design method
Manufacturing system
Assembly design tasks
Synthesis

ABSTRACT

This paper proposes a novel methodology to optimize heterogeneous design tasks with competing parameters. It is based on the principle of design parameter sensitivity, taking into account the notion of robustness at an early phase of process design. The aim is to improve the quality of the assembly system in order to make it less sensitive to variations/changes of design parameters. The methodology is based on the development of: (i) analytical design task function; (ii) inner- and outer-sensitivity; (iii) design parameter sensitivity; and (iv) decision making module. The methodology is demonstrated using results involving an automotive door assembly.

1. Introduction and motivation

The design of a complex product, such as a door assembly in modern car manufacturing systems, requires the integration of multiple tasks and design parameters shared by product and process designers. Over the last few decades product development has made impressive advancements in automation and computerization with regard to design tasks using CAD/CAE/CAM systems [1–3]. Although these technologies are state-of-the-art in the industry, however, they cannot guarantee that the final product meets the requirements in terms of quality and cost. In fact those methods and tools underscore the need for systematic integration of product and process models with coupled and multiple design parameters and tasks. For example, some of the tasks necessary for remote laser welding (RLW) joining process development are [4]: (i) fixture and clamp layout design; (ii) laser joining process parameters selection; and (iii) robot scanner visibility and accessibility analysis. The quality of the joint is directly related to the part-to-part gap which is imputed to dimensional and geometric variation of stamped sheet-metal parts (*product related*) and to fixture location and tooling variations (*process related*). Further, the joining process is affected by the laser beam visibility of all stitches and the weld quality is affected by process parameters such as laser power, welding speed, and material stack-up. In addition, the robot scanner used to make the joint is affected by part visibility which might be limited due to given clamps layout and fixture design.

It has been reported that a leading challenge in delivering high quality products is the need to incorporate statistical variation model to tackle product and process variations. Research over the past few decades have demonstrated that around 65–70% of all design changes are related to product-dimensional variation [5]. It is widely recognized that geometric and dimensional variation are among the most important quality and productivity factors in many assembly processes used not only in automotive and aerospace but also in appliance, shipbuilding and other industries. A number of studies have investigated the need to enhance ideally sized and shaped CAD/CAE/CAM models by considering non-ideal part models [7]. To date, existing approaches have mainly focused on modeling product variation without integrating non-ideal parts with assembly process models. Moreover, they are usually limited to feed-forward analysis, without a comprehensive characterization of feed-back synthesis problems which are needed in order to: (i) optimize the product/process design for a given product/process variation (*robust product and process optimization*); (ii) identify failure patterns which occur often after the design has been released (*root cause analysis*); and (iii) represent the hierarchy of design tasks, used for generating the sequence and importance of parameters/tasks to minimize their interdependencies (*design synthesis*).

In a more general context, feed-forward analysis addresses the problem of identifying the impact/effect of input Key Product Characteristics (KPCs) or Key Control Characteristics (KCCs) on output key parameters; whereas, the reverse problem is faced-out by the feed-back synthesis.

The lack of a systematic feed-back synthesis approach is a major problem when dealing with complex product development. It has been reported that only 60–70% of Right First Time (RFT) is reached during the design stage [5,6]. Failures that are not predicted during the design phase can appear during ramp-up, which in turn, require engineering changes thus, leading not only to significant cost increase but also trigger delays in the launch of a new product. A comprehensive framework going toward the feed-back synthesis is provided by multidisciplinary design optimization (MDO) which

* Corresponding author.
E-mail address: d.j.ceglarek@warwick.ac.uk (D. Ceglarek).

http://dx.doi.org/10.1016/j.cirp.2015.04.028
0007-8506/© 2015 CIRP.

is a set of engineering systems design methods which handle optimization of several tasks [8]. The MDO methods aim to take advantage of the couplings and synergies between different disciplines in order to reach the global optimal design. The main objectives of the MDO are accuracy of the found solution, computation time and robustness of the optimization process (i.e., the ability to converge to an optimum from large initialization domain). MDO has been successfully applied to a wide range of applications. Recently, Balesdent et al. [9] applied MDO to vehicle launch design specifically examining product architecture/thickness optimization and product size/shape optimization. However, optimal product design does not completely satisfy the RFT paradigm. In fact, product-to-process interactions need to be addressed and coupled with product and process variation models. Current MDO approaches are limited only to product-driven analysis and optimization. Moreover, some of the MDO approaches are mainly limited to task sequencing problem, under the assumption that the task-to-task relation is given by the designer's expertise [10–12].

The main challenges associated with feed-back synthesis problems are the existence of: (i) complex and highly non-linear relations mapping KPCs to KCCs; and (ii) heterogeneous multiple design tasks with competing and coupled design parameters.

This paper develops a methodology for improving the quality of the assembly system by introducing the concept of design parameters sensitivity. The key idea is that design parameters might or might not be correlated depending on the particular instance of the corresponding KPCs and KCCs. The sensitivity of a given design parameter is introduced as a measure of the variation induced by other parameters. Intuitively, if sensitivity of the *i*th design parameter is significantly small compared to others, then it can be assumed to be sufficiently robust.

The methodology is based on the development of: (i) design task function, which describes inner-relations among design parameters; (ii) decoupling of design parameters based on the concept of inner- and outer-sensitivity; (iii) design parameter sensitivity; and (iv) decision making module.

2. Problem definition

The dimensional quality of a product is evaluated by its KPCs defined by part features (holes, slots), edge features, etc. The KPCs must be controlled within design specifications in order to ensure that product functions meet design requirements. KCCs are then designed to satisfy KPCs.

Let us assume that the set of KPCs and KCCs in an assembly process are grouped as presented in Eq. (1) where N_{KPC} and N_{KCC} are the number of KPCs and KCCs, respectively, and DP is the set of *Design Parameters*. Hereinafter, we assume that small variation from nominal (as per tolerance analysis problems) or nominal shift (as per product/process re-design) of the DPs is called *new parameter instance*.

$$\boldsymbol{KPC} = \{KPC_1, \ldots, KPC_{N_{KPC}}\} \tag{1a}$$

$$\boldsymbol{KCC} = \{KCC_1, \ldots, KCC_{N_{KCC}}\} \tag{1b}$$

$$\boldsymbol{DP} = \boldsymbol{KPC} \cup \boldsymbol{KCC} \tag{1c}$$

Let *DC* be the set of design constraints (such as, model accuracy, quality requirements), acting on a specific design task (see Eq. (2), where N_{DC} is the number of design constraints).

$$\boldsymbol{DC} = \{DC_1, DC_2, \ldots, DC_{N_{DC}}\} \tag{2}$$

$$\begin{aligned} &\boldsymbol{DT} = \{DT_1, DT_2, \ldots, DT_{N_{DT}}\} \\ &f_{T,k}(\boldsymbol{DP_{T,k}}) = 0 \\ &\boldsymbol{DP_{T,k}} = \{DP_{T,k,1}, \ldots, DP_{T,k,N_{DP_{T,k}}}\} \subseteq \boldsymbol{DP} \\ &\textbf{subject to} \boldsymbol{DC_{T,k}} = \{DC_{T,k,1}, \ldots, DC_{T,k,N_{DC_{T,k}}}\} \subseteq \boldsymbol{DC} \end{aligned} \tag{3}$$

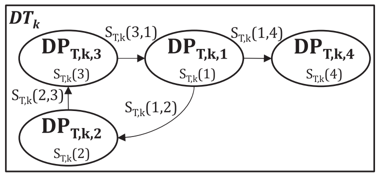

Fig. 1. Representation of the Inner Graph (IGr) and inner-sensitivity.

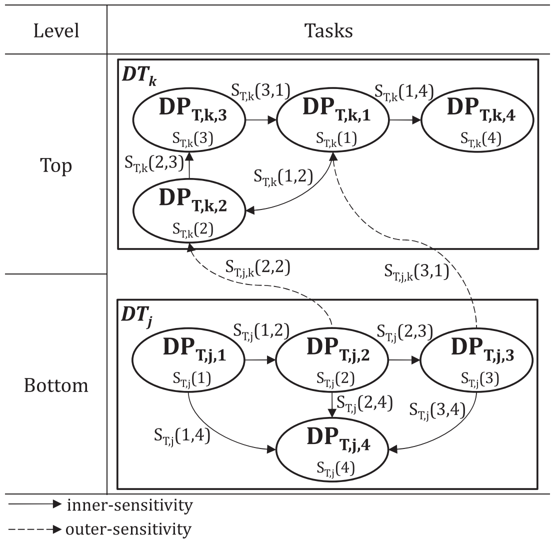

Fig. 2. Representation of the Outer Graph (OGr) and outer-sensitivity.

For a given assembly process, let **DT** be the list of design tasks, as represented in Eq. (3), where N_{DT} is the number of design tasks. Each design task links a set of DPs (i.e., $DP_{T,k}$). Subscript "T,k" indicates the subset of DPs related to a given *k*th task. "$f_{T,k}$" is the *k*th design task function.

Franciosa et al. [13] introduced the adaptive task graph (ATG) as a graph representation of possible interactions among design tasks. This paper extends the ATG concept by looking at potential interactions among design parameters for a given task (*inner-sensitivity*) or between tasks (*outer-sensitivity*) (Figs. 1 and 2).

2.1. Inner-sensitivity

Let us assume that the potential interactions among design parameters for a given task *i*th can be represented as a directed graph, called *Inner Graph* (IGr). IGr is understood as a directed graph where each node is a design parameter and the links between nodes are interactions among parameters (Fig. 1). The measure of the strength of the interaction between parameters *i*th and *t*th, for the given design task *k*th, is given by the *inner-sensitivity*, $S_{T,k}(i,t)$, which can be formally expressed as in Eq. (4a).

$$S_{T,k}(i,t) = \frac{\partial DP_{T,k,i}}{\partial DP_{T,k,t}} \; \forall\, i,t = 1, \ldots, N_{DP_{T,k}} \tag{4a}$$

Note is made here that the inner-sensitivity varies depending on the specific instance of the related DPs, because it represents the slope of the design task function "$f_{T,k}$". This implies that if for some instances the inner-sensitivity is near to zero then the corresponding interaction is neglected.

2.2. Outer-sensitivity

The concept of Inner Graph can be extended to task-to-task interaction by means of the *Outer Graph* (OGr). Fig. 2 shows a general representation of OGr, linking tasks *j*th to *k*th.

Based on the definition of hierarchy among tasks as presented by Franciosa et al. [13], lower tasks (*bottom level*) share parameters