Measuring the Objective Complexity of Assembly Workstations

Definition and Analysis of Production Complexity

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***Abstract* — The large number of product variants, produced to satisfy customers, increases significantly the complexity of manufacturing systems. As a consequence, new approaches to deal with production processes are required. Because of the impact of complexity on productivity, it is in the first place important to understand what complexity is and what are its main drivers. Based on real data, a model is suggested to characterize workstations complexity. The model is presented and its validity and accuracy are discussed. This paper defines complexity in a production environment and it proposes an identifier for complex assembly workstations. This definition is able to characterize different manufacturing systems and to define a system as high complex or low complex.**

Keywords: Complexity; Complexity Definition; Mixed-model Assembly Line

I. INTRODUCTION

Over the last couple of years, in automotive industry, the number of introductions of new and different car models has increased drastically. These new models are mainly introduced to answer consumers' needs [1], but also because of the new generation of electrical driven products.

The increase of product variety is necessary to answer the market and sustainability demands, however this high variety makes the mixed-model assembly lines become rather complex. The introduction of new models increases the complexity of (re)designing factory processes and workstations, and consequently increases significantly the overall complexity of the production system.

Currently, one can conclude that the elements presented above, increase the manufacturing complexity but the exact causes and impacts on manufacturing processes are still unknown. This paper proposes a clear and objective definition of production complexity and attempts to determine its main drivers. To this end, the drivers of complexity are determined and a model is proposed enabling to define the complexity of a workstation.

The approach used is based both on theoretical and practical information, i.e. as a result of literature study and interactions with manufacturers. Section II presents a brief literature review and describes complexity in the manufacturing domain. In Section III, a complexity definition is proposed and the methodology of the study is presented. Section IV presents the results obtained and discusses some perspectives. The conclusions and future work are presented in Section V.

II. LITERATURE REVIEW

Lately, there has been a growing interest in the study of complexity of manufacturing processes and systems [2] [3]. One can distinguish three types of complexity: product complexity, process complexity and operational complexity. According to literature, one of the influencing factors of complexity is the manipulation of information. Complexity is directly related to the quantity of information, diversity of information and the information content [4]. The human element is also important [5] since it influences system performance. Moreover, complexity increases with the number of different product variants to be produced and the number of tasks within the production process [4].

In an attempt to understand complexity, its main drivers are determined and a taxonomy is proposed. The drivers of complexity are identified as: uncertainty, dynamics, multiplicity, variety, interactions and interdependencies [6] and a combination of such proprieties can render a system complex or not complex. A specific taxonomy is proposed where complexity is split in static and dynamic [7]. Static complexity is associated with the product, whereas dynamic complexity is linked to the process.

Although until now different approaches have been developed associating manufacturing complexity to product, process and human operator, it should be emphasized that there is to the best of our knowledge no existing model that quantifies the relationship between complexity as perceived by the operators and its drivers. This is the focus of this paper. In the following section a definition of complexity within the domain of this work is introduced.

III. PRODUCTION COMPLEXITY DEFINITION AND METHODOLOGY

The research on which this paper is based was carried out within the vehicle industry of Belgium and Sweden, including both OEM's and their suppliers. The focus is therefore on workstations along a driven assembly line, which work on different vehicle models in a mixed model fashion. The research was subsequently carried out in three steps.

A. Complexity Definition

A good definition of complexity has to be generic enough to be applicable to different manufacturing systems and at the same time specific enough to guide the decision whether a system is complex or not. Although the literature review provided useful insights about manufacturing complexity, there still existed a need for a clear, simple and generic complexity definition. After extensive communication with the project partners the following definition is proposed:

"*Complexity is the sum of all aspects and elements that makes a task or a set of tasks mentally difficult, error-prone, requiring thinking and vigilance and inducing stress*".

This definition recognizes the fact that complexity of tasks is determined to a large extent by the person that executes them, hence termed subjective complexity. In many cases the same set of tasks can be judged differently by different people under different circumstances. This makes quantifying complexity in an unambiguous manner, the objective complexity, a real challenge. This paper focuses on how to measure complexity in an objective, repeatable manner.

B. Model Building Workshops

A series of workshops was done in collaboration with a group of automotive manufacturers, to gather knowledge about complexity in industry. Components of complexity were identified and classified as drivers or impacts and used to build a model.

Those workshops were a great opportunity to study and explore real manufacturing situations where complexity is present. In order to be able to gather as much useful information as possible, the participants included shop floor employees, production engineers, quality controllers and line management, who deal with complexity in their daily activities. All workshops were organized in a similar way:

Initially, the project objectives were explained to all participants. Next, the participants were asked to identify some low and some high complex workstations. Afterwards, three sets of open questions were presented to them and during a limited period of time they could reflect individually how these questions applied to the low and high complex cases respectively.

The goal of presenting the questions was to situate and identify how complexity is experienced. The questions were structured in three different sets. The first set focused on characterizing complexity. The second set of questions concentrated on revealing which consequences complexity has. The questions focus on the areas that are affected by complexity and on the influence of complexity on manufacturing work and teams. The third set of questions aimed at detecting the direct drivers of complexity, i.e. the variables that are directly linked to the complexity elements as causal factors.

Finally, after the participants' individual analysis, a brainstorming session was done where a list of ideas were discussed and gathered.

As the result of these workshops a high amount of important information was produced. In the next subsection, a causal model is presented as an outcome of the investigation of this information.

C. Causal model

As a result of the workshops, a causal model is defined with the goal to obtain a generic complexity model.

The model clusters the variables related with complexity

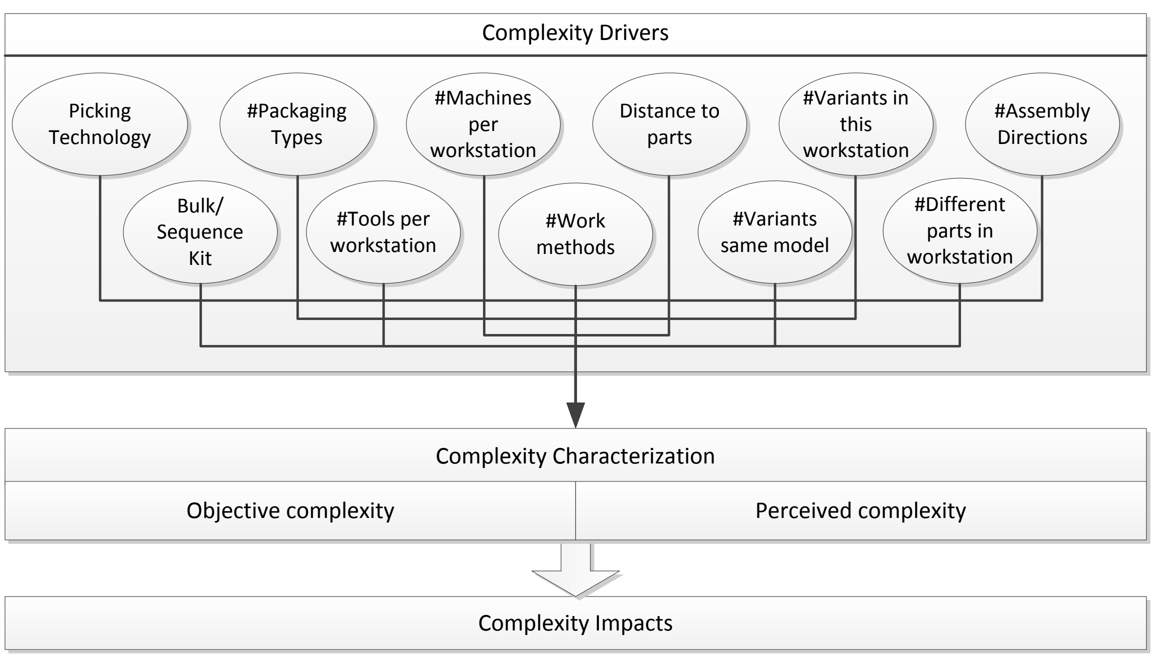

Figure 1. Complexity Causal Model

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characterization (first set of questions), complexity impacts (second set of questions), and complexity drivers (third set of questions) into groups. Fig. 1 shows how the three categories of variables are linked together. As a result of the workshops, a causal model is defined with the goal to obtain a generic complexity model.

The model clusters the variables related with complexity characterization, complexity impacts, and complexity drivers into groups. Fig. 1 shows how the three categories of variables are linked together.

Complexity drivers are the variables that are linked with the source of complexity and are therefore represented at the top of the figure.

Next, complexity characteristics describe complexity. These characteristics are clustered into 2 main groups: objective complexity and perceived complexity. The main difference between both groups is that objective complexity can be analyzed quantitatively on external values, while perceived complexity can only be studied through the cognitive behavior of the operators. The authors decided to focus their research on the objective measurement of complexity. The subjective complexity was studied by a separate team in Sweden.

Finally, complexity impacts were derived from objective and perceived complexity.

IV. RESULTS

The information obtained through the workshops was thus structured in a highly detailed causal model. Fig. 1 only shows an extract of the model, detailing the 11 direct drivers of complexity that were identified. These were further investigated.

A. *Complexity drivers*

The list of complexity-driving variables is presented in Table I together with a concise explanation of each variable. The next question to tackle was to characterize the relation between these variables and complexity, in an attempt to build a model. This set of variables is crucial to recognize what increases or decreases complexity. In order to now develop an objective complexity identifier for work stations, a dataset was created with the collaboration of the participants of the workshops.

TABLE I. COMPLEXITY-DRIVING VARIABLES

Complexity-driving variables	Description
Picking technology	Fixed (F) : Operator takes part always on the same location from bulk storage. Signal (S) : Operator picks part from location indicated by a signal (light, display) Comparing (C) :Operator must compare simple information (symbols, colors) Manual (M) : Operator must read extensive information from manifest
Bulk/Sequence Kit	Sequenced (S) : Every part is in its package in correct assembly sequence Kit (K) : Parts are delivered in kits with exact set for one assembly operation Bulk (B) :Parts are by type in their own package
# Packaging types	The total number of different packaging types, a type having a specific layout. So 2 identical boxes with different inserts are 2 different types.
#Tools per workstation	The number of tools that the operator(s) need to handle to perform all possible assembly variants in this station, automatic tools (servants) excluded.
# Machines per workstation	Machines that perform automated tasks without operator assistance, with automatic or manual start.
# Work methods	Every unique set of work methods the operator must master in this workstation. A method contains several small steps.
Distance to parts	The farthest distance between the normal operator position (or the center of the workstations) and the parts at the border of line.
# Variants same model	The highest number of variants belonging to one model, among all models of which parts are assembled in this workstation.
# Variants in this workstation	Total number of variant parts, summed over all models that are assembled in this workstation.
# Different parts in workstation	Total number of unique part references that are assembled in this workstation, including all variants and models that typically occur in one year.
# Assembly directions	The number of different positions the operator must take to complete his workstation cycle, including repositionings of the upper body or the feet, but not small repositionings of the hands.

B. ***Experimental Dataset***

Using the list presented in Table I, the manufacturing collaborators were asked to select five workstations and define the value for each variable (driver). Moreover they were asked to classify each workstation as low complex or high complex. The result is a dataset composed of 76 workstations, 41 classified as low complex and 35 classified high complex, and the respective driver values.

In order to have more control over the scaling of each variable, we set up a Likert scale for each variable, dividing the data range over 4 levels on the scale. The result is shown in Table II.

TABLE II. DIRECT DRIVERS SCALE

Complexity-driving variables	Likert scale			
Picking technology	F	S	C	M
	1	2	3	4
Bulk/Sequence Kit	S	K	B	
	1	2	3	
# Packaging types	1	2-4	5-8	>8
	1	2	3	4
#Tools per workstation	1	2-4	5-8	>8
	1	2	3	4
# Machines per workstation	0	1	2	>2
	0	1	2	3
# Work methods	0-2	3-5	6-8	>8
	1	2	3	4
Distance to parts	0-1	1, 1-2	2, 1-4	>4
	1	2	3	4
# Variants same model	1	2-3	4-5	>5
	1	2	3	4
# Variants in this workstation	1	2-4	5-10	>10
	1	2	3	4
# Different parts in workstation	1-4	5-10	11-20	>20
	1	2	3	4
# Assembly directions	1	2-3	4-5	>5
	1	2	3	4

C. Initial Model

A complexity measurement is developed based on a weighted sum of the 11 variables. This measure determines if workstations have a low or high complexity according to equations 1 and 2:

$$\text{basic complexity}(w) = \sum_{i=1}^{n} \frac{\text{score(i)*weight(i)}}{\sum_{i=1}^{n} weight(i)} \tag{1}$$

$$\text{complexity(w)} = \frac{\text{basic complexity(w)} - \sum_{i=1}^{n} \min i}{\sum_{i=1}^{n} \max i - \sum_{i=1}^{n} \min i} \;.10 \tag{2}$$

where:

- basic complexity(w) is the complexity score of a workstation *w*,
- Score(i) is the value of the variable i according to the Likert scale,
- Weight(i) is the weight of the variable *i*,
- max i is the maximum score value for variable i,
- min i is the minimum score value for variable i,
- complexity(w) is the complexity score of a workstation normalized into a scale from 0 to 10.

Fig. 2 shows the result of the calculated complexity measure compared with the subjective labels of LOW and HIGH complexity for each of the 76 workstations. The score for the LOW complexity workstations averages 4,8 and HIGH averages 7,2. The calculated score seems to distinguish HIGH from LOW complexity workstations, so the variables it is based on do seem to have a relation with the subjective complexity level. However, there is quite some fluctuation in the complexity scores. This suggests that not all variables have the same explanatory power, or even that some variables contradict others. Therefore, the next step is to adjust the weights or reduce the number of variables. In the following subsection a statistical model is developed to achieve just that.

D. Statistical model

The objective is to determine a good model for the prediction of the complexity of a workstation (high or low), based on the data gathered for the 76 work stations and their characterizing values for each of the 11 variables shown in Table I. Since the independent variable ‘complexity’ is a binary variable – it is either high or low – Logistic Regression is chosen for the analysis. In the analysis a prediction 0 corresponds to a high complex station, whereas

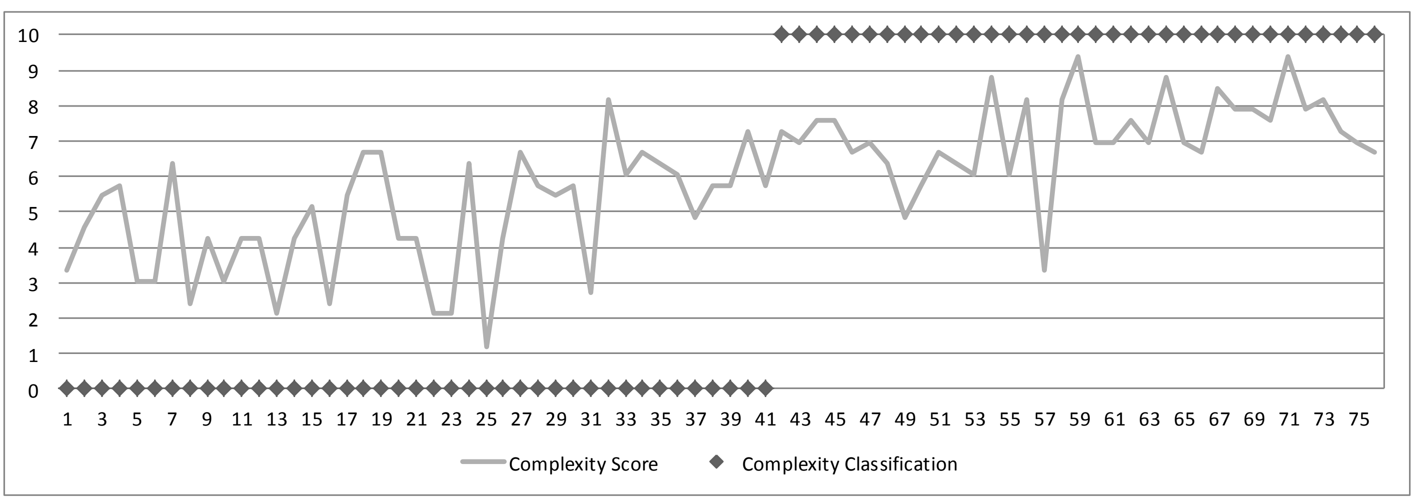

Figure 2. Workstations identification – Initial Model Versus Initial Classification

a prediction 1 corresponds to a low complex station.

Logistic regression will calculate the probability that the workstation's complexity is high or low from a combination of variable values in the following way:

$$Odds = \frac{P}{1-P} = e^{A+BX}$$
$$Ln(Odds) = A + BX = a + b_1 x_1 + b_2 x_2 + \dots \quad (3)$$

Where,

- P the chance to have a low complex station
- 1-P the chance to have a high complex station
- a a constant
- b_n coefficient for variable n
- x_n value for variable n

Based on all 76 cases, a model could be found with only 4 of the variables, able to classify 84% of all 76 cases correctly. The output is presented in TABLE III.

In the output, it can be seen that the predictive variables are:

- the Likert scale value for the number of packaging types,
- the number of assembly directions as measured directly
- the Likert scale value for the number of different parts in the workstation
- the number of work methods as measured directly

Of the 35 workstations identified as high complex, 31 could correctly be predicted as high complex by the model. Of the 41 workstations identified as low complex, 33 could correctly be predicted as low complex by the model. Fig. 3 shows the results.

TABLE III. STATISTICAL MODEL

Classification Table[a]

Observed			Predicted HIGHLOW High	Predicted HIGHLOW Low	Predicted Percentage Correct
Step 1	HIGHLOW	High	31	4	88,6
		Low	8	33	80,5
	Overall Percentage				84,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df
Step 1[a]	@#Packagingtypes	-1,127	,592	3,622	1
	Assemblydirections	-,243	,193	1,591	1
	@#Differentpartsinworkstation	-,874	,348	6,300	1
	Workmethods	-,058	,028	4,491	1
	Constant	6,676	1,837	13,200	1

V. CONCLUSION AND FUTURE WORK

This paper proposes a definition of production complexity wide enough to characterize different manufacturing systems and at the same time specific enough to define a system as high complex or low complex. A set of complexity direct drivers is extracted from real production data and interactions with manufacturers. Based on this set of complexity direct drivers two different complexity models are developed with the goal to measure and determine if workstations have a low and high complexity.

An initial model is proposed based on a complexity measure score. Then a statistical model is proposed based on logistic regression. To validate the proposed models, a set of experiments were carried out based in a set of 76 workstations which were classified as low or high complex. Initially this set contained 41 workstations classified as low complex and 35 workstations classified as high complex. The initial model was able to classify 82% of the

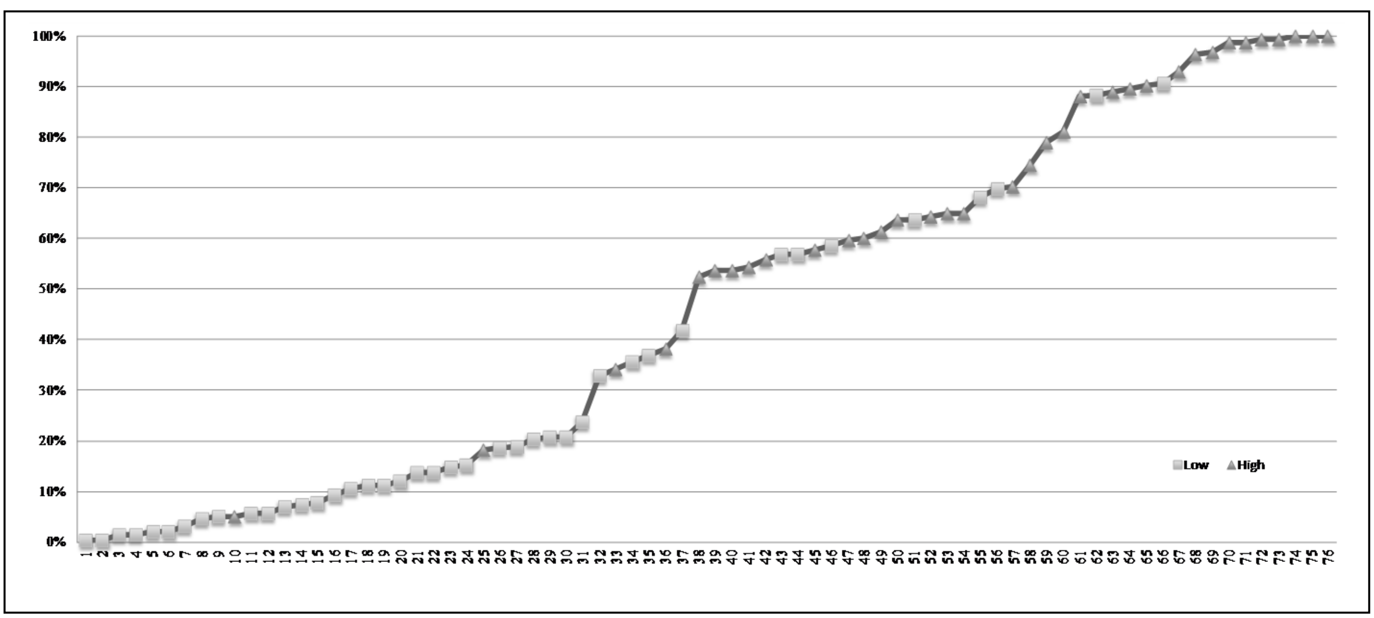

Figure 3. Workstations identification – Logit Model Versus Initial Classification

workstations correctly and the statistical model 84% of the workstations correctly.

The results obtained by the two models, provide some insight into the complexity-driving variables and their related scores. The results could also be used to measure the impact of complexity on both direct and indirect costs. They can also be useful for the subjective interpretation of complexity by the operator in the workstation.

The models give important insights in the impact of certain complexity drivers. Using the information from the models one should look into the extreme cases with wrong subjective labels, to assess whether the subjective label is wrong or not. In the former case this will enhance the value and validity of the models, and yield information about the subjective reasoning that led to the wrong classification. In the future the validity of the models should be further studied.

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