# Interaction between complexity, quality and cognitive automation

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**Abstract:** Today's assembly systems are adapting to the increased mass customisation. This means shorter cycle times, more variants and a more complex environment for the operators. An industrial case study has been performed in order to describe relations between complexity, quality and cognitive automation. This article use quantitative methods to describe the complex environment. This is done in order to create a better understanding for the importance of using cognitive automation as an enabler in order to create a more competitive assembly system for the future.

**Keywords:** Assembly, Complexity, Quality, Cognitive automation, LoA

**1. Introduction**

The future holds a more customized market. Complexity related to the increased number of product variants induced by mass customization has huge effects on the final mixed model assembly lines in modern factories. This leads to more unique products and a more complex work environment for the operator who will assemble the products, case studies show that 90 % of final assembly tasks are still performed by humans [1]. One definition of complexity is by Weaver [2] whom defines complexity as the degree of difficulty to predict the system properties, given the properties of the systems parts. Schleich means that a driver for assembly system complexity is the high variety of products and parts [3]. Similar ideas can be found by Urbanic et al. which, presents a model of complexity were quantity, diversity and content of information is direct associated with complexity [4]. The focus in this paper is the complexity related to mass customization i.e. caused by an increase of number of products and parts to assemble (increased amount of information). To meet requirements from mass customization, many assembly systems are using a mixed-model assembly approach as an enabler for the high variety of products. Although mixed model assembly is an enabler for high variety, such systems tend to get very complex as variety increase [5]. An important aspect of complexity is the "perceived complexity". From an operator point of view this is a subjective factor such as competence and information [6]. Cognitive help tools are seen to reduce the perceived complexity by supporting competence and information.

The increased task complexity in assembly needs to be handled otherwise the quality of the product and productivity in the system could be affected. In order to maintain high quality and reduce the complexity, one solution could be to consider cognitive automation for the operator e.g. technical support to know how and what to assemble and to be in situation control. An industrial case study has been executed in order to investigate the effects cognitive automation have on quality, in terms of assembly errors, in a complex final assembly context.

The aim of this paper is to:

*Investigate if cognitive automation can be used to increase quality in a complex final assembly context.*

An industrial case study has been executed to test if there is a relation between cognitive automation, quality and quantitative (objective) station complexity.

**2. Case company**

Volvo Car Corporation manufacturers around 400 000 cars per year. The two main assembly plants are located in Gent, Belgium and in Torslanda, Sweden. In the Torslanda plant five models; V70, XC70, S80, XC90 and V60 are produced with a total volume of 136 323 cars for the year 2010. The five models are based on three different platforms.

One serial flow mixed-model assembly line is used for all five models in the final assembly plant. The assembly line is divided into different line segments, which can have buffers in between. A driven conveyor line continuously paces a majority of the assembly line segments. The assembly is characterized by short cycles at each station and a high division of work. The current tact time (September, 2011) is about 66 seconds but can vary between the different line segments. To some extent subassembly lines are also used at different parts of the line. At the sub-assemblies other tact times may be used.

*2.1 Selected area*

In order test the aim of the paper, an area of interest was selected. The area is one of the most complex in the final assembly with a very high product variety and a large number of parts. The chosen area consists of a total number of sixteen stations were seven have been studied within this project (the grey operators in figure 1 represents the chosen stations). The chosen stations are a part of the pre-assembly area for the preparation line of engines. In the line the engines are customised with correct driveshaft, cables etc. The engines assembled are used in all models and variants on the main assembly line. There are three areas for the pre-assembly of the engines and this is the second area, Power Pack 2 (PP2).


**Figure 1.** Selected area, total number of stations and selected stations

The layout of the pre-assembly area is organized as a serial flow assembly line without buffers between the stations. A driven assembly line conveyor paces the line. The assembly line is characterised by short tact times, currently 63,2 seconds, and a high number of different product variants and a large number of different parts. There is one operator working at each station. Both sides of the line are used resulting in that two stations can use the same line range but on different side of the assembly object. Some stations utilize both side of the line, which for instance can be due to large size components.

The work organization is designed so that one team is responsible for 6-8 stations. There is one team leader within each team. The operators rotate between the stations in the team. For the stations chosen in this study a total number of two teams are involved as seen in figure 1. All of the investigated stations are considered to be complex due to the large number of variants and parts.

## 3. Quantitative methods used

Three different measurements have been used to verify the hypothesis of this paper namely; operator choice complexity, assembly errors (quality) and cognitive automation. How these measurements have been gathered is explained in the following sections. Data have been gathered in the final assembly plant at Volvo Cars in Torslanda, Sweden during the summer and autumn of 2011.

### *3.1 Operator Choice Complexity*

The complexity in mixed-model assembly caused by the high levels of variety is by Hu et al. called "Operator Choice Complexity" (OCC), which concerns all choices that the assembly operator can make and the risk for error associated with these choices [5]. The measurement of complexity at each station that is used for comparison in this paper is the operator choice complexity proposed by Hu et al. [5] and Zhu et al. [7]. The model can be used to calculate a complexity measure for mixed-model assembly lines.

The complexity model is based on entropy function. A definition of the operator choice complexity that is induced by product variety is given as follows: *Complexity is the average uncertainty in a random process i of handling product variety, which can be described by entropy function* $H_i$ *in the following form:*

$$H_i (P_{i1}, P_{i2,} ..., P_{iMi}) = -C\sum^{Mi}_{j=1} P_{ij} \log P_{ij} \qquad \text{(Eq 1)}$$

where $P_{ij}$ is the occurrence probability of a state $j$ in the random process $i$, $j \in [1\ Mi]$, $C$ is a constant depending on the base of the logarithm function chosen. If $\log_2$ is selected, $C = 1$ and the unit of complexity is *bit* [5].

*Equation 1* is used to calculate the operator choice complexity for each of the seven selected stations. Input to the equation is the number of variants that occurs at each station and the demand for each variant based on 3835 cars produced during one week. The probability $P$ is calculated for each variant $j$ and for each station $i$ and the total operator choice complexity is calculated with the entropy equation 1. The result for each station $i$ is presents in figure 2. The unit scale in the figure is bit.

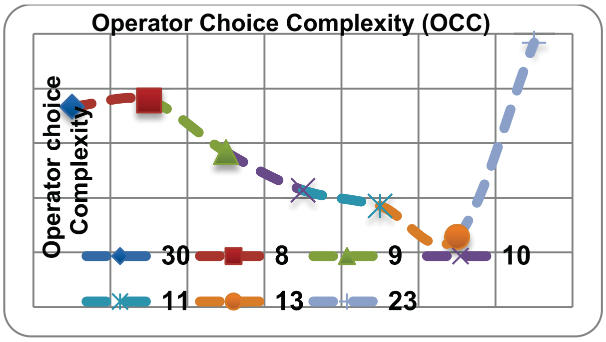


**Figure 2.** Operation choice complexity result in the chosen stations

Other complexity parameters such as number of tools, parts and tasks to perform have been gathered, seen in table 1. These parameters is used as a complement to the OCC measure. The parameters have either been collected through direct observations at the assembly line or the balancing and sequencing system used at Volvo Car Corporation.

**Table 2. Complexity parameters related to each station**

| Station number | 30 | 8 | 9 | 10 | 11 | 13 | 23 |
|---|---|---|---|---|---|---|---|
| Number of Parts* | 15 | 23 | 20 | 14 | 18 | 15 | 12 |
| Number of Tools | 2 | 3 | 3 | 4 | 5 | 3 | 2 |
| Number of Tasks** | 14 | 22 | 26 | 17 | 15 | 25 | 17 |

* Sequenced parts seen as one
** Mean value of two products

### *3.2 Assembly errors*

Assembly errors are discovered at control stations or directly by the operators at the assembly stations. All errors are reported by team leaders or by responsible quality personnel. The errors are connected to the product architecture. This means that even if a problem is discovered downstream from where it actually occurred it can be traced back to station, responsible team and individual operator causing the error.

Errors reported to the internal quality system have been extracted for a time period of 16 weeks from the system and sorted by station. The results are presented in table 2. The errors have been cleared from errors caused by material and parts defects i.e. only assembly errors are included. The errors found had the following characteristics:

**Table 3.** Type and number of errors

| Error type | Number of errors | Percentage |
|---|---|---|
| Not Connected | 106 | 30% |
| Incorrectly fitted | 83 | 24% |
| Missing | 51 | 14% |
| Not tightened | 38 | 11% |
| Total | 278 | 79 % |

Assembly errors are categorized in eleven categories, were the top four categories accounts for (278) 79% of the total number (353) of errors. These categories are associated with errors were parts not have been connected properly, incorrectly assembled or that the parts are missing or not tightened correctly. Other quite common errors are that parts are loose or that e.g. plastic covers have not been dismantled.

### *3.3 Cognitive Automation*

In order to measure the cognitive level of the station a components of a method called DYNAMO++ was used. The DYNAMO++ method [8] and a concept model [9] for task allocation were developed during 2007-2009. The main aim is to evaluate and analyse changes in an assembly system due to triggers for change i.e. the company's internal or external demands and Levels of Automation (LoA). The LoA analysis is done at working place level [10] i.e. on task, in stations [11, 12] and from an operator's perspective.

The measurement parameters used for task allocation is a seven by seven matrix [8], seen in figure 3, further developed from Frohm's taxonomy [13].

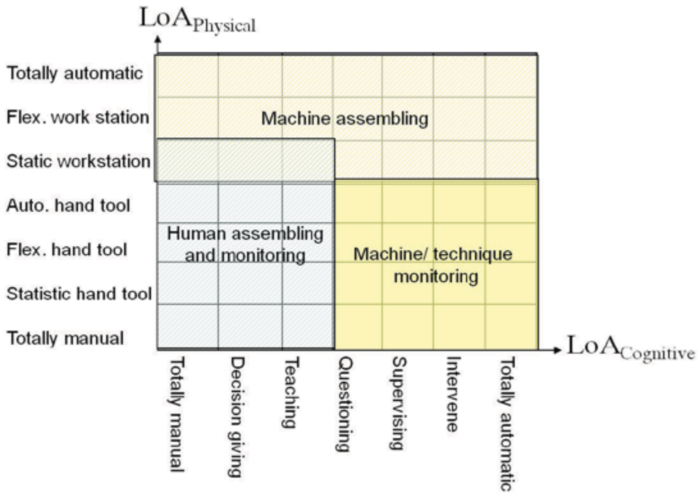


**Figure 3**. LoA matrix [14]

The LoA measure was made from direct observations and from standardised assembly instructions. An advantage of the use of two sources of information is that the standardised assembly instruction does not always correspond with the reality, which we wish to capture. Two models were assessed for each station, the most common model (C) regarding demand and the heaviest model (H) to produce regarding time. The distributions of the tasks for the two models are presented in the matrix illustrated in figure 4.

Results show that 62 percent (H) and 64 percent (C) were made with LoA level= (1;1) i.e. by hand and with own experience. The fact that so many tasks are done without cognitive support could have an impact on quality. Further, 25 percent (H) and 24 percent (C) is done with $LoA_{cog}$ =5 (often Pick-By-Light or indicators of what bit to use for the pneumatic screwdrivers). These are examples of tools, which are used to guide the operator to make a correct action and avoid errors.

*Examples of the different cognitive support tools (levels of cognitive automation) used at the stations*

The parts are presented to the operators in the material facade in bulk packages or by sequence racks (which could be seen as cognitive automation because they are sorted i.e. $LoA_{cog}$=2=working order). Many different sizes of the bulk packages are used in the façade. Poka-yoke solutions such as Pick-By-Light systems, illustrated in figure 5, are used for some parts but not all, see table 3.

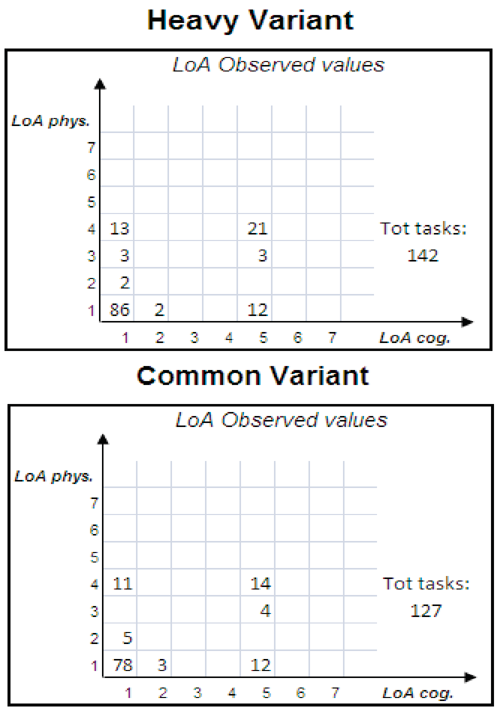


**Figure 4**. Illustration of Levels of Automation (LoA) measured at all the seven stations

**Figure 5**. Pick-By-Light, an example of cognitive automation, $LoA_{cog}$=5

Operators are supported in their work by screens, which show current model and variant and status of required tightening operations. The operators are also provided with feedback from the Pick-By-Lights and haptic feedback from some of the tools used. Operator instruction sheets are available at every team area gathered in binders. Both manual tools and automated tools are used in the assembly work.

**Table 4. Nr of tools and cognitive support used at the stations**

| Station | 30 | 8 | 9 | 10 | 11 | 13 | 23 |
|---|---|---|---|---|---|---|---|
| Number of Tools | 2 | 3 | 3 | 4 | 5 | 3 | 2 |
| Number of PBL | 7 | 15 | 13 | 0 | 6 | 3 | 5 |
| Sequenced articles | 0 | 0 | 0 | 1 | 1 | 1 | 1 |

### 4. Relations between the three areas

In order to answer the hypotheses an investigation between four relations (illustrated in figure 6) has been done and is discussed in following sections.

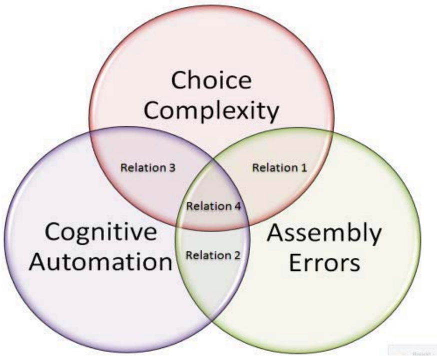


**Figure 6.** Overview of the three investigated areas

*4.1 Relation 1; between operator choice complexity and assembly errors*

The first relation between the operator choice complexity and the assembly errors is illustrated in figure 7. As seen there is a relation between the lowest complexity and the lowest number of assembly errors (Station 13) and vice versa (Station 23). Station 11 differs the most from the pattern that the assembly errors follows the measure of OCC. Therefore these three stations have been further compared in the other relations.

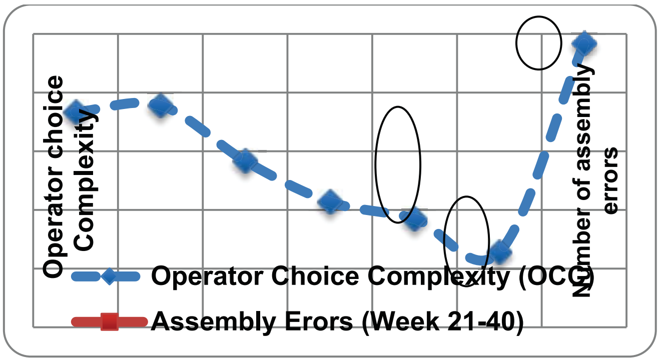


**Figure 7**. Relation between operator choice complexity and assembly errors

*4.2 Relation 2; between assembly errors and cognitive (and physical) automation*

The station that sticks out is station 11, if assembly errors had a correlation with OCC the anticipated number errors found would have been approximately the half, why is it so high?

Due to the fact that over 60 percent of the tasks are done with own experience and that *"incorrectly fitted"* and *"not connected"* has the highest assembly errors in the further investigated stations (11,13 and 23), a summary of the assembly errors is shown in table 4, could be an indicator that there is a need for more cognitive support within these stations.

**Station 11**

A total of 241 assembly errors were found during the investigated time period. 181 assembly errors were excluded due to that these errors were associated with errors from a supplier and not the assembly operation. Leaving the total number of errors for the investigated time period to 60 errors. 63% (38) of the errors were classified as *"not connected"* and one single part and task accounted for 38 % (23) of the total errors. The LoA of this specific task was (1, 1)[1]. Meaning that the operation was performed without any support.

**Station 23**

A total of 91 assembly errors were found during the investigated time period. 60% (54) of the errors were classified as *"incorrectly fitted"*. One single part and task accounted for 51 % (47) of the total errors. The part was either placed in wrong position or missed. The LoA of this specific task was (1,1). Meaning that the operation was performed without any support.

**Station 13**

A total of 10 assembly errors were found during the investigated time period. They were all classified as *"not connected"*. The low error rate at this station could be explained by that most operations at the station were associated with a high LoA. Part assurance was made with a hand scanner and tightening operations were counted by the system to match the number of tasks supposed to be performed.

**Table 5. Summary of errors at station 11, 23 and 33**

| Error Code | Nr. of errors (station 11) | Nr. of errors (station 13) | Nr. of errors (station 23) | Total nr of errors |
|---|---|---|---|---|
| Incorrectly fitted | 4 | - | 54 | 58 |
| Not Connected | 38 | 10 | 5 | 53 |
| Not Tightened | 2 | - | 19 | 21 |
| Missing | 14 | - | 5 | 19 |
| Total | 60 | 10 | 91 | 161 |

*4.3 Relation 3; between operator choice complexity and cognitive automation*

The choice complexity is directly influenced by the choices and variance of solutions. An increased number of models, parts, tools etc. will result in an increase of choice complexity. Table 5 shows the number of variants and the demand of the most common variants. The choice complexity measure cannot directly be reduced by cognitive automation. However, introducing cognitive automation can reduce the perceived complexity caused by the increased choice complexity.

**Table 6. Complexity elements**

| Objective Complexity Elements | Station 11 | Station 13 | Station 23 |
|---|---|---|---|
| OCC | 3,9 | 3,8 | 4,5 |
| Number of tools | 5 | 3 | 2 |
| Number of variants | 31 | 27 | 51 |
| Demand for each variant | 8 variants accounted for 77 percent | 9 variants accounted for 78 percent | 6 variants accounted for 51 percent |

At the investigated stations decision support is given by Pick-By-Light and process support is given by monitors and tools associated with tightening operations. Tightening tasks are easy

[1] Not observed during the LoA assessment assessed afterwards

to control and restrict while assembly operation, which is done without any use of a tool, are very hard to monitor and control. Many manual tasks on the stations were to connect electrical connections. However neither decision nor process support was given when performing contact operations. The information regarding these operations was to be found in binders at the stations. If the contact operations are missed or badly performed the error is not acknowledged until on later control stations while tightening operations are controlled within the station boundaries by a control system connected to the tools.

*4.4 Relation 4; is there a relation between cognitive automation, quality and quantitative (objective) station complexity?*

Earlier empirical results [15] show that in general, system complexity, does affect performance negatively and that training and that man/machine interface plays important roles in minimizing the negative effect of system complexity on performance.

Results from previous sections show that relations could be made between quality, complexity and cognitive automation. Believes are that cognitive automation can be used as a mean to reduce the negative effects of choice complexity in terms of quality.

**5. Conclusion**

This paper shows that it is possible to use quantitative measures in order to show relation between station complexity, quality and cognitive automation. These methods could be further used in order to improve both the resource efficiency and resource allocation in order to get an effective assembly system. Then, the operators' competence and experience should also be taken into consideration, which is not fully covered by using the three methods.

The main conclusion is that there is evidence that cognitive support is needed in final assembly to minimize the negative effects of complexity.

**Acknowledgment**

The authors like to express their gratitude to all involved personal at the case study and the collages within the COMPLEX project. This work has been funded by Vinnova within the program Production Strategies and Models for Product Realization.

This work has been carried out within the Sustainable Production Initiative and the Production Area of Advance at Chalmers. The support is gratefully acknowledged.

**References**

[1] Fasth Å, Stahre J. Does Levels of Automation need to be changed in an assembly system? - A case study. Proceedings of the 2nd Swedish Production Symposium (SPS). Stockholm, Sweden, 2008.

[2] Weaver W. Science and Complexity. American Scientist 1948;36:536.

[3] Schleich H, Schaffer L, Scavarda F. Managing Complexity in Automotive Production. 19 th International Conference on Production Research, 2007.

[4] Urbanic RJ, Waguih H, ElMaraghy HA. Modeling of Manufacturing Process Complexity, 2006.

[5] Hu SJ, Zhu X, Wang H, Koren Y. Product variety and manufacturing complexity in assembly systems and supply chains. CIRP Annals - Manufacturing Technology 2008;57:45-48.

[6] Gullander P, Davidsson A, Dencker K, Fasth Å, Fässberg T, Harlin U, Stahre J. Towards a Production Complexity Model that Supports Operation,Re-balancing and Man-hour Planning. Proceedings of the 4th Swedish Production Symposium (SPS), 2011.

[7] Zhu X, Hu SJ, Koren Y. Modeling of Manufacturing Complexity in Mixed-Model Assembly Lines. Journal of Manufacturing Science and Engineering 2008;130.

[8] Fasth Å, Stahre J, Dencker K. Measuring and analysing Levels of Automation in an assembly system. Proceedings of the 41st CIRP conference on manufacturing systems Tokyo, Japan, 2008

[9] Fasth Å, Stahre J. Concept model towards optimising Levels of Automation (LoA) in assembly systems. Proceedings of the 3rd CIRP Conference on Assembly Technologies and Systems. Trondheim, Norway, 2010.

[10] Westkämper E. Digital Manufacturing in the global Era. Proceedings of the 3rd International CIRP Conference on Digital Enterprise Technology. Setúbal, Portugal, 2006.

[11] Nyhuis P, Kolakowski, M. H, C. L. Evaluation of Factory Transformability. 3rd International CIRP Conference on Reconfigurable Manufacturing. Ann Arbor, USA, 2005.

[12] Wiendahl H-P, ElMaraghy HA, Nyhuis P, Zäh MF, Wiendahl H-H, Duffie N, Brieke M. Changeable Manufacturing - Classification, Design and Operation. Annals of the CIRP 2007;56:783-809.

[13] Frohm J, Lindström V, Winroth M, Stahre J. Levels of Automation in Manufacturing. Ergonomia IJE&HF, 30:3 2008.

[14] Fasth Å, Lundholm T, Mårtensson L, Dencker K, Stahre J, Bruch J. Designing proactive assembly systems – Criteria and interaction between Automation, Information, and Competence. Proceedings of the 42nd CIRP conference on manufacturing systems Grenoble, France, 2009

[15] Guimaraes T, Mårtensson N, Stahre J, Igbaria M. Emperically testing the impact of manufacturing system complexity on performance. International Journal of Operations & Production Management 1999;19:1254-1269.