The effect of learning factors due to low volume order fluctuations in the automotive wiring harness production

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Abstract

In the automotive wiring harness industry the manual assembly is very common, especially in the companies producing a big variety of products and low production volumes. Moreover, small, intermittent and even occasional orders result the fact that production is always at the start-up phase. Therefore, the processing time is not stable, fluctuates and thus planning becomes a complex issue. This paper proposes the method of calculating the impact of learning at the complicated planning situations and indicates that planning which omits learning factors is the major source of bottlenecks and other efficiency loses in the manual assembly. The authors of this research believe that good understanding of the learning impact due to manufacturing fluctuation on the particular production expressed in quantitative indicators will provide significant information for the decision making and improve the robustness of planning and control process in this way; finally, will represent how costly bad decisions could be.

Keywords: manual assembly; learning curves; production planning; operating time

1. Introduction and problem definition

As the world of manufacturing continues to move from mass one towards LEAN production [1], many manufacturing companies are becoming order-based manufacturing systems. It was already reported in [2] that order-based manufacturing companies have a lot fewer possibilities to control their own production. Customer demand could arrive at random and long-time intervals and manufacturing system has to cope with unplanned growth in the quantities of orders. The supplier has little chance to impact the customer, because the market is tough and the competition is high. The company’s manufacturing system has to be extremely flexible and efficient to react and fulfill the customer orders with precise delivery, perfect quality and low product costs. The creation of such a flexibility and competitiveness is one of the major order-based manufacturing issues. Failure to solve these flexibility issues leads to extreme sensibility to customer demand fluctuations when the customer in order to solve their own planning issues might alter the demand sharply thus reducing orders to the minimum and forcing the supplier to keep unused capacity or reduce staff. Later on, the customer might increase demand, and then if the staff have been already reduced, the supplier just cannot fulfill orders due to lack of capacity. Therefore, there is significant need to choose the optimal production capacity and implement improved production planning and control. It is hardly possible to guarantee flexibility for the complex production processes, because changing the production cells for a specified product requires the re-design of the whole technological process; however, some flexibility improvement even can be implemented on such cases.

The manual assembly is being widely replaced by robotic and automated equipment; however there still exist production fields where human work is inevitable due to a variety of reasons. The automotive wiring harness industry is the particular manufacturing field where the manual assembly is very common. Wiring harness production might be manual,
semi-automatic and robotic (fully automatic) depending on production volume [3,4]. Therefore, wiring harness manufacturers producing a big variety of products with lower production volumes naturally perform manual assembly.

In typical mass production, order quantities are huge and therefore start-up (learning) phase is soon completed. Even in the order-based manufacturing systems, when order quantities are stable and large [5] the start-up phase is soon completed. However, when the order quantities are small, intermittent and/or occasional, there is no possibility of completing the start-up phase, so production is always at the learning stage, even if the manufacturing is regular. As the result, the processing time is not stable, fluctuating is also much higher than the expected steady-state production time and, therefore, production planning and control in such a situation becomes very complex and even the effect of the learning becomes unknown.

The goal of this research is to propose the model of evaluation of the extent of which the fluctuating quantities, prototype production, poor planning, unplanned customer orders effect the processing time due to learning factors in the manual demand-based wiring harness industry. The study is based on the working environment of a particular wiring harness manufacturer and all references apply to this specific manufacturer. This company does not design or create its own product; it belongs to the automotive industry supply chain, so it must manufacture the wiring harnesses strictly according to customer drawings, specifications and standards and has no possibility of changing the product structure. The manufacturing is order-based. Obviously the company suffers from the flexibility issue commonly met in order-based manufacturing. Therefore, correct understanding of the impact of the learning factors would draw the direction for production improvement thus further solving the flexibility issue stated before. This research is based on production data of the most complex manufacturing and planning situations when planning becomes chaotic just to fulfill customer orders. The collected data will be analyzed by regression analysis, to evaluate if data follows the learning model, and the direct effect of the learning will be calculated and evaluated.

### Nomenclature

- \( \alpha \) - slope coefficient
- \( \beta \) - assembly time of the first unit
- \( x \) - unit number
- \( y(x) \) - Wright learning model
- \( \mu(x) \) - Crawford learning model
- \( H(x) \) - Heaviside function
- \( m \) - Vector denoting product shift
- \( \beta \) - Vector denoting first unit production time
- \( y(x,\alpha,\beta,m) \) - Re-occurring learning model
- \( T \) - Total assembly time

### 2. Manual wiring harness assembly

In this section a short description of the main product of the company (wiring harness) is presented. Even though the main wiring harness function is electrical, it is produced by mechanical assembly: manual, semi-automatic, automatic as it was stated before. The typical wiring harness layout is represented in the drawing in Fig. 1. The main wiring harness components:

- Terminated circuits
- Housing and connectors;
- Wrapping material (tubes, hoses, tapes, etc.)
- Additional components;

The assembly is performed on the assembly jig by an operator using following steps [6]:

- Wire preparation, when wires are being cut ant terminals mounted.
- Installation, cables and branches are being placed on assembly board according the certain layout.
- Securing, cables and wires are wrapped together; protective hoses are pulled on branches and legs.
- Attachment, cables and wires with mounted terminals are being assembled into housings, connectors, splices and etc.

Since the first step is the usually automatic, only the next three steps represent manual assembly of the product. During the assembly, an operator performs series of small operations of the each step thus installing all necessary constituting components until final product is fully assembled. At the beginning of the assembly, lots of time is wasted due to the start-up phase. The operator is forced to check drawings, standards and perform other learning factors. Even if the wiring harnesses are similar, but depending on the function four major types of wiring harness exist: power cables, the common harness, the engine harness and the electrical center
harness. Assembly departments are dedicated for the certain harness type. Moreover, each harness has its own specific layout and circuit scheme. At the beginning of the assembly the operator needs to check the documentation before each assembly step: before plugging a terminal, wrapping tape, etc. So, the overall performance of the assembly process is continuously improving until the steady-state performance is reached, i.e. the operator does not need to think before installing a certain component. Obviously, small production quantities prevent the operator from reaching this steady-state performance.

The final assembly is being performed at the working cell where all necessary production resources are provided during set-up: raw materials, semi-products, tooling, assembly jig and etc. Since currently there is possibility to reduce the setup time, planners tend to avoid unnecessary or repeated setups. The manufacturing cell is dismantled and rearranged for the new product only after the previous order is fully completed.

3. Complicated manufacturing and planning situation

Order-based manufacturing without completely implemented JIT (just-in-time) technique makes planning an extremely complicated issue. When manufacturing orders are released only on customer demand and the company does not intend to produce to the stock, then stochastic demand, fluctuating order quantities and delivery times, unplanned orders, priority orders and other uneven situations (excerpt from weekly demand for selected complex product depicted in Fig. 2.) from the more than one company’s customers create chaotic planning. As a result, orders with late delivery are being terminated, shifted, delayed and new orders released to any department having free capacity.

The research [13] focused on optimal work allocation and order quantity reduces and the number of operations increases. The study [14] concentrated on optimal work schedule and optimal order size and proposed optimal deterministic planning method to satisfy the demand accurately and minimize production costs. The empirical results from the company with heavy non-linear learning effects confirmed the approach to be adequate and realistic compared with the other methods.

Some authors address similar planning issues similar to the ones in this research. The inefficiencies of traditional balanced assembly lines while coping with unequal operator

4. Learning curve application

Learning models have been known for a several decades. Initially, they were based on the study of processing time decrement as the manufacturing continues. Recently, the interest in the learning effects has increased regarding the time increment at the beginning of manufacturing [7]. In the next section the literature review regarding LC models used for the production planning is represented.

4.1. Learning curve application review

Currently, many researchers focus on a variety of issues due to learning-forgetting effects. Several authors address planning improvement using learning curves. The paper [8] addresses the processing time estimation from a limited shop floor data and concludes that estimated learning curves could be used for the better allocation of labor resources thus creating a smoother workflow at the factory through planning improvement. On the other hand, the same paper points out the lack of possibility to gain such detailed data to be used for curve fitting, because companies rarely collect and share such a data with researchers. In spite to this even limited data could be applicable and useful for learning curve application.

The work [9] used several LC models to fit the data from the sheet metal company, chose the best one and concluded that production planning with applied LC more accurately forecasts the need of labor resources. Authors [10, 11, and 12] propose some analytical and deterministic planning methods with implemented learning curves. The study [10] reported that empirical evaluation showed effective solution to the job-shop scheduling problems. In the works [11, 12] a case study was performed at the shoe manufacturing company. The results show that satisfactory workload balance and optimal schedules were achieved after implementing learning curve models into the process planning. Other works [13, 14] address the production optimization with learning models. The research [13] focused on optimal work allocation and concluded after empirical calculations that savings of LC-based work allocation grows (compared with traditional line balancing), as order quantity reduces and the number of operations increases. The study [14] concentrated on optimal work schedule and optimal order size and proposed optimal deterministic planning method to satisfy the demand accurately and minimize production costs. The empirical results from the company with heavy non-linear learning effects confirmed the approach to be adequate and realistic compared with the other methods.

The most complicated manufacturing and planning situations appear when the delivered production quantity is decreasing, but the operators are forced to work overtime. It will be later shown that the main reason causing this situation is assembly interruption and order shifting from one department to another for the most complex wiring harnesses (500 circuits and more which require the most learning time at the beginning).
speed due to learning are reported in [15]. The authors study the impact of variability to the general assembly line performance and their findings show that introduction of the new operators cause major inefficiency at the traditional assembly balancing. Also, the paper provides analytical approach to improve planning in case of variability of operators. Similar findings were reported in [16], where changing of the operators in the assembly lines due to absenteeism or planning cause bottlenecks. The paper [17] deals with ramp-up period caused by learning impact during the growth of demand and proposes a planning model stabilizing the production process and inventory levels and points out the synchronization as the major source of performance improvement. The same paper suggests that synchronization could be achieved with assigning extra operators to the assembly process. On the other hand, even skilled operators need learning phase to achieve steady-state performance. Therefore, in highly manual assembly operator shifting might not be the preferable solution. There are more authors concerning the issues caused by learning-forgetting [18].

The most of the researches report the benefits of the learning models in addressing planning issues, such as variability, changing operators, and unstable order quantities. However, there is still lack of case studies of how learning affects particular production, for instance, wiring harness assembly and also how department and operator changes impact the assembly time of a particular product in the demand-based companies with fluctuating low volume orders.

4.2. General learning curve models

Currently, plenty of different applicable learning curve models are proposed from power to exponential, as well as other more sophisticated functions [7]. However, two major models are most-widely used. The cumulative average model commonly known as Wright’s model [19]:

\[ y_w(x) = \beta x^{-\alpha} \]  

Where \( x \) is the accumulated production quantity, \( y_w \) is the total amount of labor time which is required for \( x \) units, the parameter \( \alpha \) is slope coefficient for Wright model, \( \beta \) is the number of direct labor time required to produce the first unit. The second model is the Crawford’s model often called unit model [20]:

\[ y_c(x) = \beta x^{-\alpha} \]  

Where \( x \) is the unit number, \( y_c \) is the number of direct labor time required to produce the \( x^{th} \) unit, the parameter \( \alpha \) is a slope coefficient for Crawford model.

Both models have a similar structure, and they could even be transformed into each other. On the other hand, the unit model is more accurate in calculating the direct learning effect to a certain single unit or several units, therefore the unit model will be used for further study.

4.3. Re-occurring learning model

From the product perspective, if its assembly with current technology and without any production interruptions follows the learning model (1) or (2), the effect of the learning factors is minimal even if the learning phase is not completed and the steady-state time is not reached. Any production interruption causes re-occurring learning, i.e. when the same learning factors occur several times for the same product. Then the total learning time is unnecessarily increased. Below the mathematical formulation of such a re-occurring learning model is presented. Let \( m \) is a vector denoting product shifts from one department or operator to another and \( n \) is the total number of such shifts:

\[ m^T = (m_1, m_2, m_3, ..., m_n) \]  

Let \( \beta \) is a vector denoting the processing time for the first unit at the each re-occurring learning.

\[ \beta^T = (\beta_1, \beta_2, \beta_3, ..., \beta_n) \]  

Then re-occurring learning curve is expressed as by using Heaviside function \( H(x) \):

\[ y(x, \alpha, \beta, m) = \sum_{i=1}^{n} \left[ \frac{1}{m_i} F(x, m_{i-1}, y_{i-1}) \left( \frac{x}{m_i} \right)^{-\alpha} \right] + H(x - m_{i-1}) \beta_{i-1} \left( \frac{x}{m_i} \right)^{-\alpha} \]  

And:

\[ F(x, m_{i-1}, m_i) = H(x - m_{i-1}) - H(x - m_i) \]  

In order to calculate assembly time for the whole production quantity \( N \), the derived expression (5) is summed:

\[ T = \sum_{j=1}^{n} \left[ \sum_{i=1}^{m_j} y_p(j) \right] + \sum_{j=1}^{N} y_p(j) \]  

Slope coefficient \( \alpha \) is supposed to be the same for each re-occurring learning.

5. Calculation results and discussion

To illustrate the extent of which the production disorders effect the processing time due to learning factors, one complex product the assembly of which suffered many re-occurring learning phases was selected.
After the last department change, the assembly of this particular product was thoroughly studied, the assembly time measured and shifting prevented for a half year period already, despite continuing fluctuations in customer demand. The production data of this product is presented in Fig. 3.

Using the regression analysis, Crawford learning curve model (2) was fit on the collected assembly data points. The calculation results confirm that the data follow Crawford learning. Before this product was taken to account, it was treated like any other wiring harness at the company and it was moved for several times from one department to another, the continuing order log for this wiring harness is depicted in Fig. 4.

Now using formula (5) the re-occurring learning curve will be calculated for this product. Vector \( m \) is filled according product order log:

\[
m^T = (1 \ 3 \ 10 \ 12 \ 22 \ 32 \ 34 \ 40 \ 64)
\]

For the first unit time at the vector \( \beta \) the same number obtained by regression analysis will be used (except in shifts back to the same department).

\[
\beta^T = (130 \ 130 \ 95 \ 130 \ 130 \ 90 \ 130 \ 89)
\]

Calculated model is depicted in Fig. 5. The graph contains both the re-occurring learning curve (Fig. 5 curve 2) and the learning curve with a single initial learning (Fig. 5 curve 1) for comparison.

Finally, the total learning time \( T \) is calculated for both cases: with re-occurring learning \( (T_{rl}) \) and conventional learning \( (T_{cl}) \):

\[
T_{cl} = 3443 \text{ h}
\]
\[
T_{rl} = 6683 \text{ h}
\]

Both calculation results from the graphical and numerical comparisons clearly indicate a significant difference between synchronized production (one initial learning), and chaotic production (re-occurring learning). Even a single department change unnecessarily would increase the processing time and can create a bottleneck. The calculated example shows an extreme extent when processing time due to learning increased by 1.94 times. The less complex wiring harness...
with less learning factors will be less sensitive to the department and operator change, but the impact still remains significant.

6. Conclusion

The study of a certain wiring harness manufacturer showed that the basic source of chaotic production is uneven demand and poor planning. The uneven customer demand (stochastic demand, fluctuating order quantities) boosts planning shortcomings and causes unsynchronized production. Calculation results from graphical and numerical comparison clearly indicate that the effect of unnecessary and re-occurring learning caused by manufacturing fluctuations to assembly performance is significant and increases the assembly time, especially at the fluctuating low volume orders. The proposed re-occurring learning model explains why assembly performance of certain products could be dramatically reduced. The analytical calculation model ((5) and (6)) providing quantitative information will facilitate decision making at the planning phase thus avoiding costly decisions. The planner in the situation of fluctuating order quantities often makes a decision of department change. With the implementation of proposed overall learning calculation methodology, the planner could calculate the cost and time increment due to department change and use this information for the decision making.

Further research should be addressed to the implementation of the proposed model not only for a single but for the whole range of products in the production. After calculating the total impact of learning, the study should indicate possible total learning time minimization thus further improving the robustness of planning and control processes.

References

[1] Holweg M. The genealogy of LEAN production. J Oper Manag. 2006;25(2):420-437.
[2] Barber KD, Hollier RH. The use of numerical analysis to classify companies according to production control complexity. Int J Prod Res. 1986;24(1):203-222.
[3] Aguirre E, Ferriere L, Raucent B. Robotic assembly of wire harnesses: economic and technical justification. J Manuf Syst. 1997;16(3):220-231.
[4] Aguirre E, Raucent B. Performances of wire harness assembly systems. Industrial Electronics, Symposium Proceedings IECON'94, 1994 IEEE International Symposium. 292-297.
[5] Estrada F., Villalobos JR, Roderick L. Evaluation of Just-In-Time alternatives in the electric wire-harness industry. Int J Prod Res. 1997;35(7):1993-2008.
[6] Ong NS., Boothroyd G. Assembly times for electrical connections and wire harnesses. Int J Adv Manuf Tech. 1991;6:155-179.
[7] Azizan M, Folliazzo FS. Learning curve models and applications: Literature review and research directions. Int J Ind Ergonom. 2011;41:573-583.
[8] Simant TL, Watts CA. Improving operations planning with learning curves: overcoming the pitfalls of ‘messy’ shop floor data. J Oper Manag. 2003;21(1):93-107.
[9] Gunawan I. Implementation of Lean manufacturing through learning curve modelling for labour forecast, International Journal of Mechanical & Mechantronics Engineering. 2009;9(10):46-52.
[10] Gabel T, Riedmiller M. Distributed policy search reinforcement learning for job-shop scheduling tasks. Int J Prod Res. 2012;50(1):41-61.
[11] Azizan M, Folliazzo FS. Learning curve modelling of work assignment in mass customized assembly lines. Int J Prod Res. 2007;45(13):2919-2938.
[12] Azizan M, Folliazzo FS. Scheduling learning dependent jobs in customised assembly lines. Int J Prod Res. 2010;48(22):6683-6699.
[13] Cohen Y, Vinnet G, Sarin SC. Optimal allocation of work in assembly lines for lots with homogenous learning. Eur J Oper Res. 2006;168(3):922-931.
[14] Neydigh RO, Harrison TP. Optimising lot sizing and order scheduling with non-linear production rates. Int J Prod Res. 2010;48(8):2279-2299.
[15] Montano A, Villalobos JR, Gutierrez MA, L. Mar L. Performance of serial assembly line designs under unequal operator speeds and learning. Int J Prod Res. 2007;45(22):5355-5381.
[16] Cohen Y. 2012. Absenteeism as a major cause of bottlenecks in assembly lines. Int J Prod Res. 50 (21):6072-6080.
[17] Glock CH, Jaber MY, Zolfaghari S. Production planning for a ramp-up process with learning in production and growth in demand. Int J Prod Res. 2012;50(20):5707-5718.
[18] Jaber MY, Sikstrom S. A numerical comparison of three potential learning and forgetting models. Int J Prod Econ 2004;92:281-294.
[19] Wright TP. Factors affecting the cost of airplanes. Journal of the Aeronautical Sciences. 1936;34(4):122-128.
[20] Yelle LE. The learning curve: historical review and comprehensive survey. Decision Sci. 1979;10(2):302-328.