

Learning Curves of Temporary Workers in Manual Order Picking Activities

Lernkurven von Zeitarbeitern in manuellen Kommissioniertätigkeiten

Matthew Stinson

Institut für Fördertechnik und Logistik
Abteilung Logistik
Universität Stuttgart

Person-to-stock order picking is highly flexible and requires minimal investment costs in comparison to automated picking solutions. For these reasons, traditional picking is widespread in distribution and production logistics. Due to its typically large proportion of manual activities, picking causes the highest operative personnel costs of all intralogistics process. The required personnel capacity in picking varies short- and mid-term due to capacity requirement fluctuations. These dynamics are often balanced by employing minimal permanent staff and using seasonal help when needed. The resulting high personnel fluctuation necessitates the frequent training of new pickers, which, in combination with increasingly complex work contents, highlights the importance of learning processes in picking.

In industrial settings, learning is often quantified based on diminishing processing time and cost requirements with increasing experience. The best-known industrial learning curve models include those from Wright, de Jong, Baloff and Crossman, which are typically applied to the learning effects of an entire work crew rather than of individuals. These models have been validated in largely static work environments with homogeneous work contents.

Little is known of learning effects in picking systems. Here, work contents are heterogeneous and individual work strategies vary among employees. A mix of temporary and steady employees with varying degrees of experience necessitates the observation of individual learning curves.

In this paper, the individual picking performance development of temporary employees is analyzed and compared to that of steady employees in the same working environment.

[Key words: order picking, manual performance evaluation, learning curves]

Die Person-zur-Ware-Kommissionierung weist eine hohe Flexibilität auf und ist mit geringen Investitionskosten verbunden in Vergleich zu entsprechenden automatisierten Lösungen. Auf diese Eigenschaften ist die Verbreitung traditioneller Kommissioniersysteme in der Distributions- sowie in der Produktionslogistik zurückzuführen. Aufgrund ihres großen Anteils an manuellen Tätigkeiten verursacht die Kommissionierung die höchsten operativen Personalkosten aller intralogistischen Prozesse. Die häufige Anpassung der Personalkapazität eines Kommissioniersystems als Reaktion auf kurz- und mittelfristig schwankende Kapazitätsanforderungen bedingt einen häufigen Personalwechsel. Die entsprechend oft anfallende Einarbeitung neuer Mitarbeiter in Kombination mit einer steigenden Komplexität der Arbeitsinhalte betont die Bedeutung von Lernprozessen in der Kommissionierung.

In industriellen Anwendungen werden Lerneffekte i. d. R. anhand von Zeit- und Kosteneinsparungen, die sich in Abhängigkeit mit der Erfahrung ergeben, quantifiziert. Zu den bekanntesten industriellen Lernkurvenmodellen zählen u. a. die Modelle von Wright, de Jong, Baloff und Crossman. Diese Modelle werden typischerweise zur Beschreibung von Lerneffekten einer Belegschaft statt Individuen herangezogen. Die Modelle wurden jeweils in hauptsächlich statischen Arbeitsumgebungen mit homogenen Arbeitsinhalten.

Über Lerneffekte in der Kommissionierung ist bis dato wenig bekannt. Hier sind die Arbeitsinhalte heterogen und die Arbeitsstrategien der einzelnen Mitarbeiter unterschiedlich. Eine Mischung aus kurz- und langfristig eingestellten Kommissionierern mit unterschiedlichen Erfahrungsgraden bedingt die Betrachtung individueller Lernkurven.

In diesem Beitrag wird die individuelle Leistungsentwicklung von Zeitarbeitern in der Kommissionierung analysiert. Diese wird mit der Leistungsentwicklung fest angestellter Kommissionierer im selben Kommissioniersystem verglichen.

[Schlüsselwörter: Kommissionierung, Leistungsbewertung, manuelle Tätigkeiten, Lernkurven]

1 INTRODUCTION

1.1 BACKGROUND: ORDER PICKING AND LEARNING

The VDI 3590 guideline defines picking as the compiling of item groups out of an assortment of items based on orders [VDI94]. Picking is the most important process within a distribution center and is necessary for the provision of materials to most production systems [Hom11]. The work contents are typically heterogeneous in terms of the various dimensions, masses and other properties of items that must be handled as well as the variety of additional tasks which must be performed. Such tasks may include the fulfillment of customer-specific packaging requirements or assistance in other areas, such as incoming or outgoing shipping. Due to its high degree of flexibility and relatively low investment requirements, traditional person-to-stock picking remains more common than automated solutions [Koe12].



Figure 1. *Manual person-to-stock order picking*

A picking system must also be flexible in terms of its ability to satisfy volatile capacity requirements, which are often seasonally determined, at an economically feasible cost. In order to handle short-term capacity requirement fluctuations, job rotation and floater concepts are implemented, by which workers perform various tasks based on a schedule and/or current needs. In order to constantly maintain only the base personnel capacity requirement and provide the necessary manpower when work volume is high for a period of weeks or months, the temporary employment of external workers has become popular: In 2011, the implementation of temporary, external workers in Germany rose by 20.49% to include 882,000 employees [Lük13]. In picking, new workers must be trained before an economical performance level is attained. The learning costs of a new picker encompass the following elements:

- direct training costs, such as the provision of a mentor and study materials,
- opportunity costs in terms of lost picking performance during non-operative training and be-

fore an economical performance level is attained,

- costs incurred due to picking mistakes in the form of rework and the handling of returns.

The more frequent training of temporary employees represents an absolute cost increase. Simultaneously, the shorter employment duration of temporary workers implies higher training costs relative to total employment costs. This results in a necessity for the optimization of learning processes in manual picking systems.

Learning processes in industrial settings are generally expressed as learning curves. A learning curve is understood as a decreasing time and/or cost requirement per production unit as experience increases [Yel79]. Industrial learning curve research has thus far focused primarily on group learning in static work environments with largely homogeneous work contents. This situation stands in contrast to manual picking. Here, work contents are heterogeneous and dynamic, the picking system is flexible and the individual employee has the freedom to develop and implement his own work strategy. For example, in systems without navigation guidance, workers are essentially free to pick items in whatever order they see fit. Psychological studies have revealed that strategy shifts occur during learning. The study of individual learning processes, including qualitative aspects such as strategy selection, has been best analyzed by psychological experimentation. Such studies have shown that performance can depend more heavily on an individual's work strategy than on the specific cognitive task being performed [Ang11, Del98, Rit92].

Because individual learning processes in picking have not yet been thoroughly researched, little is known of the learning processes which take place while temporary pickers' performance improves. In practice, operative and strategic management tasks are hampered: Calculating the temporary manpower requirement, evaluating the performance of learning pickers as well as comparing the costs of temporary versus steady employees in general are tasks which currently rely on a great deal of guesswork due to the lack of transparency described above.

1.2 OBJECTIVES

In this paper, methods for quantifying learning curves in manual picking are analyzed and compared. The observed learning effects are then quantitatively described using exponential modelling. The corresponding individual and group learning rates are calculated according to [Wri36] and compared. Focus in the analysis is placed on the forms of individual and average learning curves by employment type as well as their implications for the practice. The data used in this paper were kindly provided by a company in Germany which operates several cross-

docking stations throughout the country and chooses to remain anonymous.

It was hypothesized that learning curves in the observed picking system can best be displayed measuring individual performance based on processing time per pick, as this is the smallest and most homogeneous measurable unit of work. [Gro13] also use this method of performance measurement in quantifying learning curves in order picking. It was further hypothesized that the measurement of experience based on the number of orders completed, rather than on the number of days worked, would be more closely correlated with the observed learning effects. This hypothesis is based on the observation that most learning curve models consider experience based on the cumulative number of units produced, despite the tendency of practitioners to measure their employees' experience in units of time worked. It was assumed that temporary pickers would exhibit steeper learning curves than steady employees, as the former find themselves at an earlier point in the learning curve.

2 THE BASICS OF INDUSTRIAL LEARNING CURVE THEORY

Learning is defined as a sustained change process in humans and animals as well as in organizations and machines. It encompasses the acquisition of new information as well as the modification and reinforcement of existing knowledge, behavioral patterns, abilities, values and preferences [Sch11].

Operative learning effects in industrial settings manifest themselves as fewer direct work hours are needed and fewer mistakes are made per production unit [Hie91]. These gains in efficiency are achieved to a large extent autonomously through first-order learning: As workers perform repetitive movements more quickly and with fewer unnecessary steps, sensorimotor learning is taking place. This and the independent optimizations of work activities by operative employees are classified as first-order learning. Second-order learning encompasses improvements implemented by management, such as training and reorganization and is often based on realizations gained through primary learning. Initially, secondary learning processes typically disrupt and negatively impact performance; however, additional primary learning and performance gains are ultimately attained. Thus, primary and secondary learning processes interact, as shown in Figure 2 [Adl91].

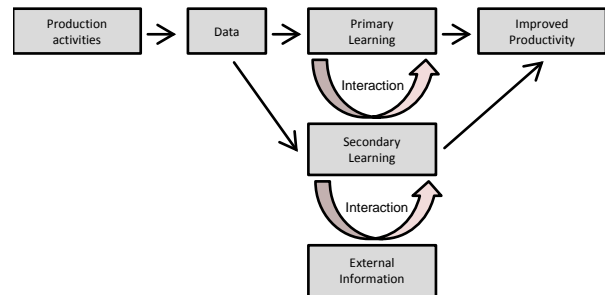


Figure 2. General industrial learning model [Adl91]

The majority of learning curve studies can be classified into one of two categories:

- empirical studies in industrial settings or
- experimental studies in psychology.

In industrial learning curve research, price rather than cost data are often utilized, as the latter are less readily available. The resulting market-side approach to quantifying learning effects is referred to as the *experience curve* [Laa05]. Learning curves are generally implemented in operational personnel planning, cost prognosis and short-term controlling tasks; the experience curve is typically taken into consideration for long-term strategic considerations [Hen84, Spe81, Yel79].

[Wri36] constitutes the first widely read scientific study on learning curves in an industrial setting. The article shows that the production costs per airplane decreased at a constant rate in relation to the plant's experience, measured in terms of airplanes produced. Specifically, it was determined that, with each doubling of the cumulative number of airplanes produced, the same percentage of cost savings per airplane is achieved [Wri36]. The resulting logarithmic-linear relationship serves as the basis for various other learning curve models and enjoys the broadest practical use due to its simplicity and widespread applicability [Jab04, Fog11, Smu11]. Learning curve models can generally be classified as one of the following model types:

- log-linear,
- exponential,
- hyperbolic and
- multivariate [Fog11].

The application of the more sophisticated learning curve models offers greater predictive power, but is often precluded by the unavailability of the necessary data, particularly in the case of multivariate learning curve models [Bad92]. An illustration of the classic learning curve models, which are also the most widely used, is provided in Figure 3 on a logarithmic scale.

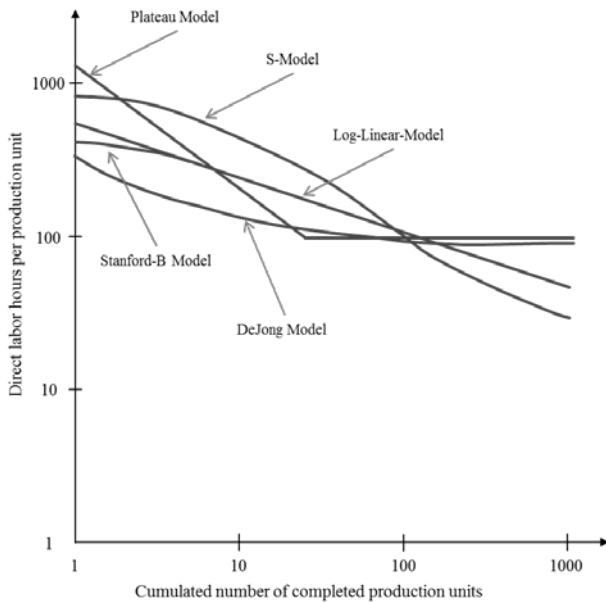


Figure 3. Classic learning curve models [Yel79]

3 QUANTIFYING THE LEARNING CURVE IN ORDER PICKING

3.1 MEASURING PERFORMANCE IN MANUAL PERSON-TO-STOCK ORDER PICKING

Learning curves are generally drawn based on data pairs by which measurements of time (x-axis) are linked to measurements of experience (y-axis). Thereby, the measures of time are usually denoted by the cumulative average or current amount of direct labor – measured in units of time or cost – required per unit of production. If the measured unit of work is highly heterogeneous, care must be taken in order to avoid comparing the processing time required for highly dissimilar picks, lines or orders. Orders vary in terms of the number of lines and picks they contain as well as the corresponding item locations, masses and volumes, which necessitate differing amounts of physical exertion in the form of walking, lifting and handling. If a sufficient level of homogeneity is present at the pick level, i. e. if items are similar in size and mass and their storage locations are equally distributed, the average processing time required per pick for each order may be a sufficient indicator of performance.

In order to reduce distortion of the learning curve due to highly heterogeneous work contents, individual standard times can be calculated for each production unit. Learning effects can then be measured by comparing the standard processing times to the actual processing times required by learning employees. An example is provided in Figure 4.

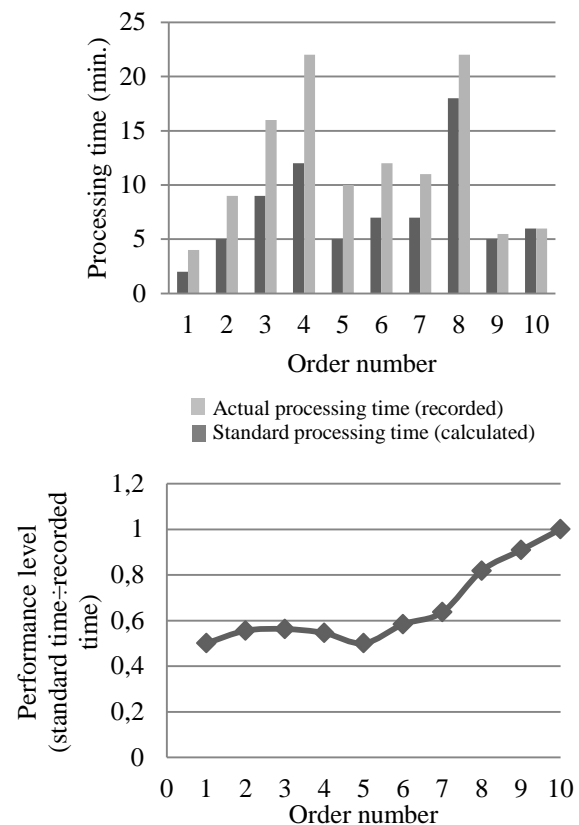


Figure 4. Learning effects as performance development curves

If standard times must be calculated per order for personnel planning purposes, it may be necessary to consider multiple variables. [Sti14] use multiple regression analysis in order to consider the number of picks and lines as well as the required walking distances and the mass transported for each order. This method relies on historical data, however, and is thus not directly applicable to learning employees. Another method of calculating standard times in manual processes such as traditional picking is the application of systems of predetermined standard times such as MTM (Methods-Time Measurement) and REFA (Reichsausschuss für Arbeitszeitermittlung). These tools offer a high degree of accuracy, but require significant know-how in order to be implemented. The time blocks and algorithms created when applying these tools are picking system-specific and must be updated accordingly with each change to the picking process. A practical problem associated with the use of standard times in measuring learning effects is the method's incompatibility with the learning curve models discussed; the result is a positively sloped performance development curve rather than a typical negatively sloped learning curve.

3.2 THE OBSERVED PICKING SYSTEMS

For the quantification of learning curves, picking data from a company which employs temporary external workers on a seasonal basis were utilized. The data reflect picking performed by nine steady and 40 temporary employees over the course of approximately eight months. This time period represents the entire employment span for most of the temporary employees. The data were collected at one of the company's several a cross-docking stations. The number of orders processed fluctuates very little while the number of lines contained in each order fluctuates moderately. The number of picks per line and order is highly volatile and to a large extent seasonally dependent. The items picked are generally of similar sizes and can be easily picked up with one hand. Picking at the cross-docking station is performed in two steps: the bringing of items to the picking stations and the fulfillment of orders using these items, the latter of which step is stationary. The two steps are performed by different employees and the timestamps utilized in this paper are produced by the employee performing the stationary order fulfillment activities.

3.3 ANALYSIS OF THE DATA

Raw data were collected from the company's warehouse management system and structured in a relational database. Data analysis was performed by querying this

database. Performance was measured on a per order basis as the average processing time per pick. This method was chosen because of the homogeneity of the picks and especially due to the fact that picking is performed at stationary picking bases. The measurement of time per pick also allows for the application of standard learning curve models (see section 3.1).

Exponential modelling of the learning curves in the observed picking system reveals that the majority of the performance variations observed for the steady employees cannot be described based on either investigated measure of experience alone. The most common criticism of [Wri36] lies in the model's implication of infinite learning [Fog11]. The inability to precisely model the performance development of highly experienced pickers suggests that this criticism is warranted in the case at hand.

Exponential modelling of the temporary employees' learning effects yields a good fit ($r^2=0.79$) if experience is measured in days rather than in the number of orders completed. This observation contradicts the hypothesis stated in section 1.2. It suggests that learning curves in order picking, where no assembly line or pacemaker process determines a takt time, are inherently different from the classical industrial learning curves seen in mass production environments. The results of the exponential modelling are summarized in Table 1 by employment type.

Performance measurement	Experience measurement	r^2	
		Steady employees	Temporary employees
Cumulative average seconds/pick	Days worked	0.27	0.79
Cumulative average seconds /pick	Orders completed	0.35	0.44

Table 1. Explanatory power of exponential modelling in the observed picking system by employment type

As evidenced by Figure 5, the performance levels of steady and temporary employees overlap within a few days, suggesting that temporary pickers are able to quick-

ly attain the average picking performance level set by steady pickers under normal conditions.

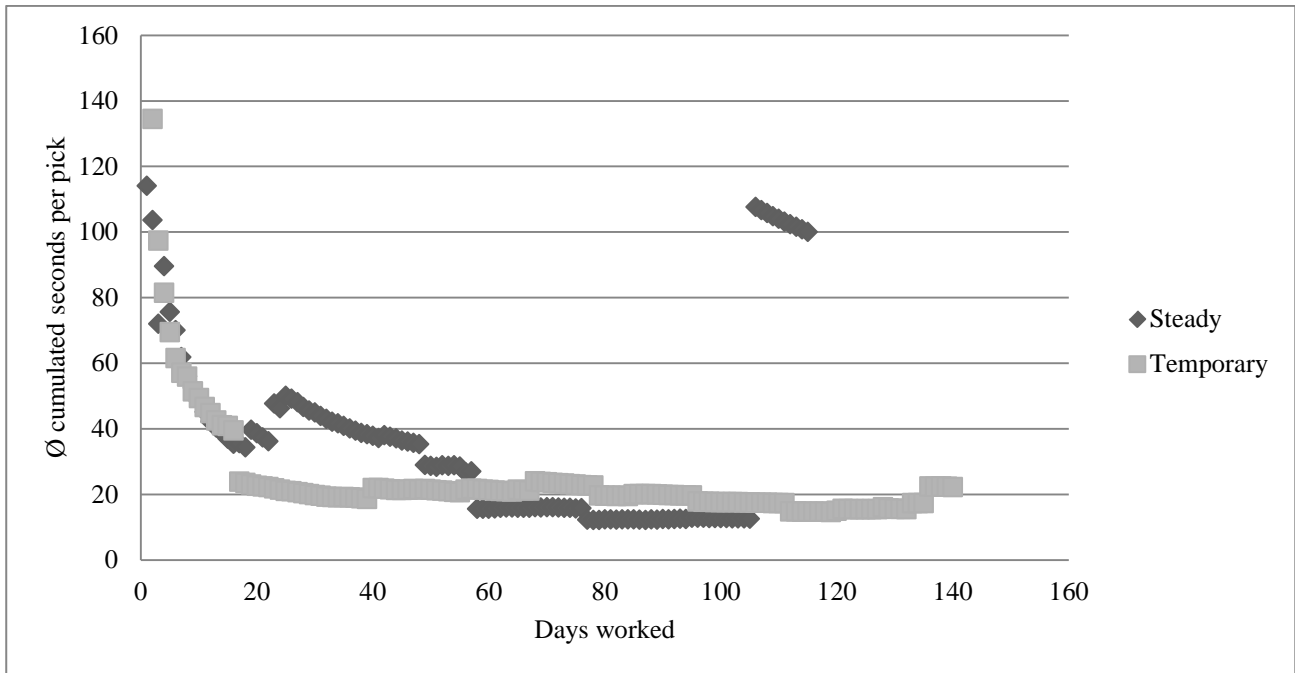


Figure 5. Average learning curves by employment type and number of days worked

The average steady employee picking times by days worked significantly undercut those of temporary employees when both learning curves have flattened out at approximately 60 workdays. Individual performance levels of the temporary employees are synchronized by date in Figure 6. Here, it is evident that learning was fastest at

the beginning of the observed timeframe. Learning is slowest and performance indeed decreases from mid-February to mid-April. It should be noted that order volume is highest from October through January, during which timeframe capacity and performance per employee was relatively high and a great deal of learning took place.

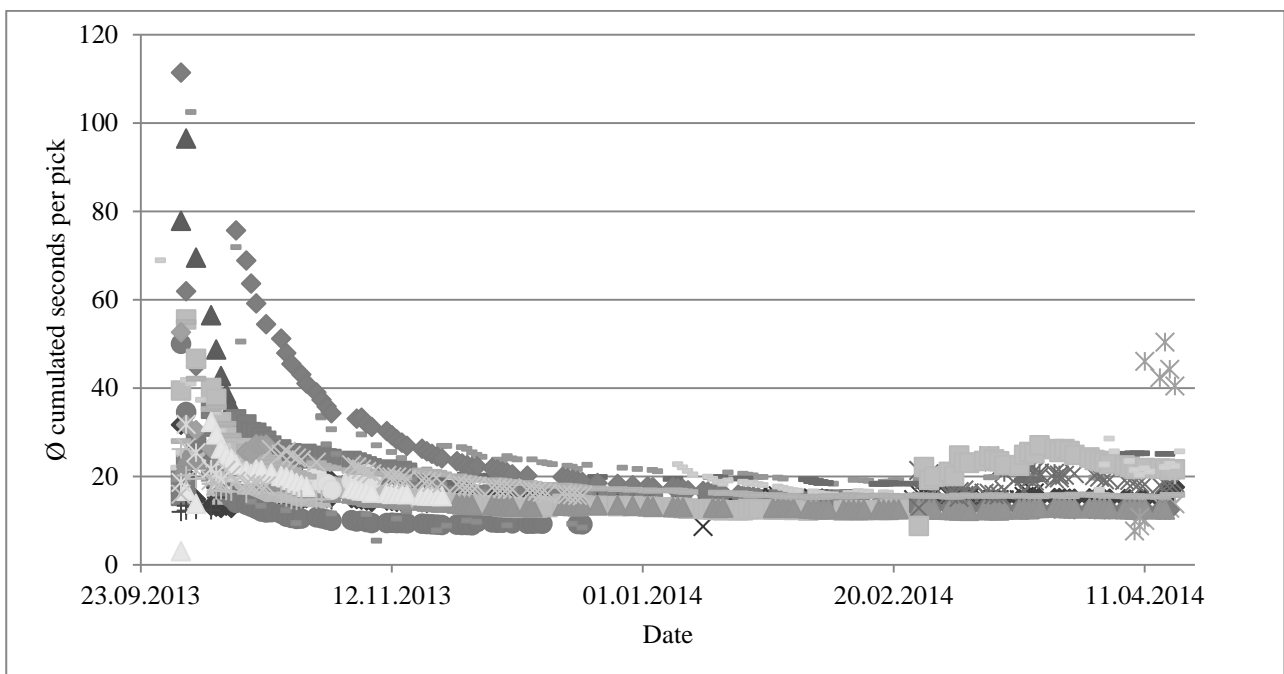


Figure 6. Individual learning curves of temporary workers by date

In Figure 7, the learning curves of temporary pickers are displayed in terms of individual experience based on

the number of orders completed. Here, the individual learning curves exhibit less variation from one another, as

individual experience has been synchronized along the x-axis. The synchronization of the individual learning curves by experience provides more transparency than the exclusive observation of a macro-learning curve. In the former case, the arbitrary consolidation of individual

learning curves of various maturities is avoided. The relatively long picking times required for the first orders indicates that significant performance improvements were attained within the first day of work.

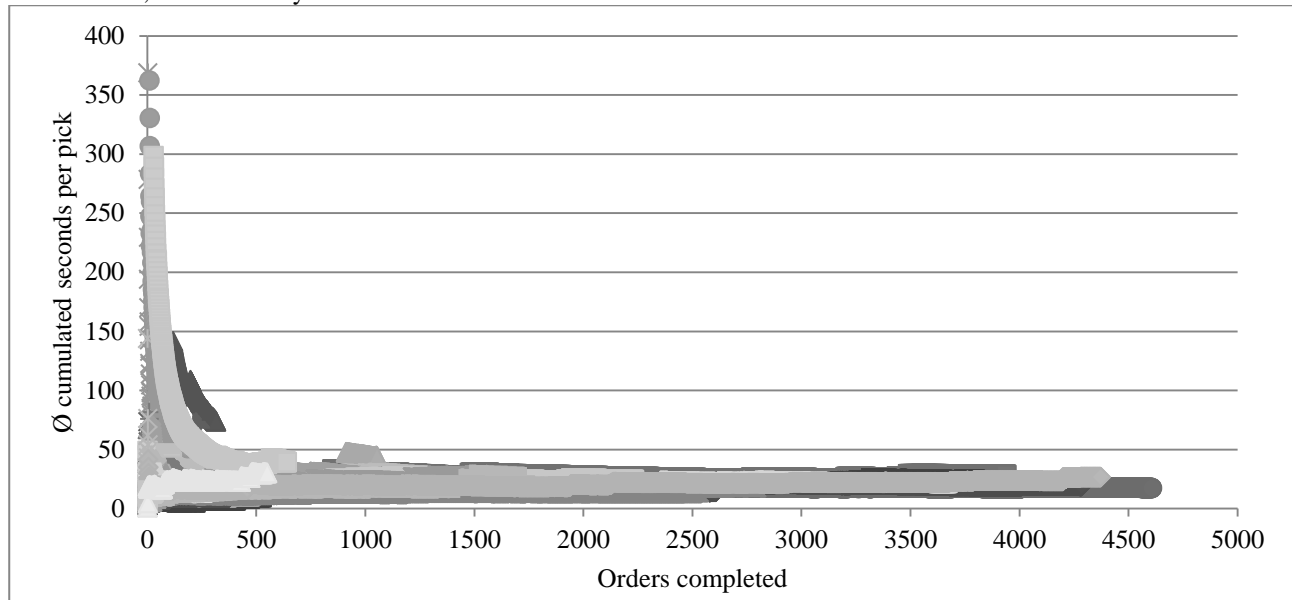


Figure 7. Individual learning curves of temporary workers by number of orders completed

The learning rate expresses the percentage of the original input time that will be required to complete one order upon the doubling of the cumulative number of orders picked [Wri36]. Thus, lower learning rates signify faster performance improvement. A learning rate of one indicates no progress while learning rates of greater than one indicate increasing time requirements within the observed experience interval. The learning rates were calculated for all employees for each day worked. Calculating

the learning rates from day to day rather than from order to order allows for more measurement points to be considered between intervals. The results, summarized in Table 2, indicate that temporary workers learned on average faster than steady employees. It is also shown that the average learning rate of temporary employees is more volatile than that of steady employees.

	Learning rate	Standard deviation	Highest average learning rate of an employee	Lowest average learning rate of an employee
Ø Steady employees	94.3%	12.3%	120.5%	77.9%
Ø Temporary employees	89.8%	32.2%	201.1%	50.1%

Table 2. Learning rates of temporary and steady employees

4 CONCLUSION AND OUTLOOK

The findings presented here show that learning effects in the observed picking system are best measured in terms of the required time per pick by workdays completed. The learning effects of temporary employees can be modelled exponentially with a good degree of precision for at least 4,500 orders or approximately 140 workdays. The analysis of steady, experienced employees shows that the majority of the observed performance variances cannot be explained based on experience alone. It is suggested that these variations are determined in part by other factors, such as the general workload volume and work pressure.

The results indicate that the experienced workers at some point attained a steady state, during which the learning curve stagnates, supporting the findings of [Coc60]. The ability of the steady employees to significantly undercut average picking times for extended periods of time, however, suggests that learning may continue while the higher performance capability is called upon on an as-needed basis. Specifically, steady employees typically attained higher performance levels when the work volume was highest.

Analysis of the observed picking system for the same time period in the next year would reveal whether performance continued to improve among steady and temporary employees. Of particular interest would be whether returning temporary employees are able to quickly reclaim

their previous performance levels. Such insight into the effects of breaks and the forgetting associated therewith would be of interest not only for the selection of temporary workers based to an extent on this criterion, but also for companies which implement job rotation concepts in picking.

Future research on learning curves in picking should focus on the development of methods for using learning curves in strategic and operative management tasks, especially when the nature of the work is more heterogeneous than in the case at hand. With more detailed picking data from additional picking systems, modelling techniques which do not rely on cumulative performance values could be developed.

Gefördert durch:



Bundesministerium
für Wirtschaft
und Technologie

aufgrund eines Beschlusses
des Deutschen Bundestages

Das IGF-Vorhaben 17658 N / 1 (LeiKom) der Bundesvereinigung Logistik wurde über die AiF im Rahmen des Programms zur Förderung der Industriellen Gemeinschaftsforschung (IGF) vom Bundesministerium für Wirtschaft und Energie aufgrund eines Beschlusses des Deutschen Bundestages gefördert.

LITERATURE

- [Adl91] Adler, P.; Clark, K.: *Behind the Learning Curve: A Sketch of the Learning Process*. In: *Management Science* 37, 3, 1991, p. 267-281
- [Ang11] Anglim, J.: *Strategies in skill acquisition: reconciling continuous models of the learning curve with abrupt strategy shifts*. University of Melbourne, 2011
- [Bad92] Badiru, A.: *Computational Survey of Univariate and Multivariate Learning Curve Models*. In: *IEEE Transactions on Engineering Management* 39, 2, 1992, p. 176-188
- [Coc60] Cochran, E.: *New Concepts of the Learning Curve*. In: *The Journal of Industrial Engineering* 11, 1960, p. 317-327
- [Fog11] Fogliatto, F.; Anzanello, M.: *Learning Curves: The State of the Art and Research Directions*. In: Jaber, M., Ed., *Learning curves*. CRC Press, 2011, p. 3-22
- [Gro13] Grosse, E.; Glock, C.: *An experimental investigation of learning effects in order picking systems*. In: *Journal of Manufacturing Technology Management* 24, 6, 2013, p. 850-872
- [Hen84] Henderson, B.: *The Application and Misapplication of the Learning Curve*. In: *Journal of Business Strategy* 4, 1984, p. 3-9
- [Hie91] Hieber, W.: *Lern- und Erfahrungskurveneffekte und ihre Bestimmung in der flexibel automatisierten Produktion*. Vahlen, Munich, 1991
- [Hom11] ten Hompel, M., Sadowsky, V., Beck, M.: *Kommissionierung: Materialflusssysteme 2: Planung und Berechnung der Kommissionierung in der Logistik*. Springer, Heidelberg, 2011
- [Jab04] Jaber, M.; Kher, H.: *Variant versus invariant time to total forgetting: the learn-forget curve model revisited*. In: *Computers & Industrial Engineering* 46, 4, 2004, p. 697-705
- [Koe12] Koether, R.: *Distributionslogistik: Effiziente Absicherung der Lieferfähigkeit*. Gabler, Wiesbaden, 2012
- [Laa05] Laarmann, A.: *Lerneffekte in der Produktion*, University of Bochum, 2005
- [Lük13] Lüken, S.: *Arbeitsmarkt: Stabile Entwicklung in unsicheren Zeiten*. Statistisches Bundesamt, 2013. – URL http://www.destatis.de/DE/Publikationen/STATmagazin/Arbeitsmarkt/2013_01/2013_01Arbeitsmarkt.html
- [Rit92] Ritter, F.: *What determines initial feeling of knowing? Familiarity with question terms, not with the answer*. In: *Journal of Experimental Psychology: Learning Memory, and Cognition* 18, 3, 1992, p. 435-451
- [Sch11] Schacter, D.; Gilbert, D.; Wegner, D.: *Psychology* 2nd ed. Worth Publishers, New York, 2011
- [Smu11] Smunt, T.: *Log-Linear and Non-Log-Linear Learning Curve Models for Production Research and Cost Estimation*. In: Jaber, M., Ed., *Learning curves*. CRC Press, 2011, p. 91-102

- [Spe81] Spence, M.: *The Learning Curve and Competition*. In: *The Bell Journal of Economics* 12, 1, 1981, p. 49-70
- [Sti14] Stinson, M.; Sommer, T.; Wehking, K.-H.: *Bewertung und Optimierung der Effizienz manueller Tätigkeiten in der Kommissionierung (EfKom)*, research project report, 2014. – URL http://www.bvl.de/files/441/481/522/Abchlussbericht_17236N_FS1.pdf
- [VDI94] VDI: *Kommissioniersysteme - Grundlagen*. Beuth Verlag, Berlin, 1994
- [Wri36] Wright, T.: *Factors Affecting the Cost of Airplanes*. In: *Journal of Aeronautical Sciences* 3, 4, 1936, p. 122-128
- [Yel79] Yelle, L.: *The learning curve: historical review and comprehensive survey*. In: *Decision Sciences* 10, 2, 1979, p. 302-328

Matthew Stinson, M.Sc, MBE, Research Assistant in the Department of Logistics at the Institute for Materials Handling and Logistics of the University of Stuttgart, was born in 1983 in Chicago, U.S.A. He obtained his bachelor's degree from Hendrix College in 2006 in Economics and German Studies as well as master's degrees from Pforzheim University in 2011 and the University of Stuttgart in 2013 in Industrial Engineering and Logistics Management, respectively.

Address: Institut für Fördertechnik und Logistik, Universität Stuttgart, Holzgartenstraße 15b, 70174 Stuttgart, Germany
Phone: +49 711 685-83475, Fax: +49 711 685-83769,
E-Mail: matthew.stinson@ift.uni-stuttgart.de