CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2022

3rd Conference on Production Systems and Logistics

Process Data Validation For Manual Assembly Systems Used For Highly Variable Products

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Abstract

The production of customized goods is becoming more and more important for industrial companies. The large number of variants resulting from this, up to batch size 1 production, requires a high degree of flexibility. To meet these requirements, manual production processes are frequently still used. This is especially applicable to the area of assembly. Data acquisition is a significant task in manual assembly due to volatile secondary activities and alternative handling operations. The process times to be recorded are also influenced both consciously and unconsciously by the employees. This paper describes an approach for the validation and interpretation of production data of manual assembly systems. Therefore, process data are analysed based on the use case of terminal strip assembly in the learning factory of the Chair of Production Systems at the Ruhr-University Bochum is presented. Here, the validation of the product data from 2021 is carried out by checking the data for normal distribution. This is followed by an analysis of the data with regard to the effects of spikes. Furthermore, the influences of a low data basis, different degrees of standardization and learning effects in the course of production are analysed. Finally, a discussion on the findings and further procedures will take place.

Keywords

Process time acquisition; Production planning; Manual assembly; Factors of influence; Validation

1. Introduction

Industrial production is increasingly subject to the change from a supplier's to a buyer's market. Product life cycles are becoming shorter and the number of product variants is increasing. [1, 2] In addition, labour costs are rising and demographic developments are leading to a shortage of skilled workers [3]. In connection to the increasingly demanded of high flexibility and adaptability, this means a great challenge for manual assembly. In the field of manual assembly, there is still no automated acquisition and real-time-capable evaluation of production data for dynamic production control [4, 5]. One reason for this is that manual operations are often used where tasks change volatilely and a high degree of adaptability is required. In addition to these workflows, which are rather difficult to predict, individual approaches of people also predominate. Often, a lack of standardization in SME production environments is an additional factor here. Finally, data acquisition must not mean any additional work for employees, in order not to increase the proportion of secondary activities. Furthermore, the privacy rights of employees must be given priority.

In this conflict, both the continuous data acquisition and subsequent filtering as well as the interpretation of the KPIs do not mean a proper representation of the production system. In addition to the high process diversity and changing environmental conditions, the diverse human factors, such as motivation, learning

DOI: https://doi.org/10.15488/12165 publish-Ing.

behaviour and fatigue, pose a particular challenge for analysis and conclusions. Especially the acceptance of production data acquisition systems in production environments dominated by humans requires accurate data and key figures. With regard to the validation and analysis of data, there are approaches in the area of automated machines. The data captured automatically by means of sensors can be examined with regard to trends and distribution functions. Furthermore, approaches such as the DOE are state of the art in the analysis of technical systems. [6] Here, individual parameters of the systems can be varied and examined with regard to their model. This is not possible in the real production process of a manual assembly.

For this reason, in this paper an approach for the validation and interpretation of production data of manual assembly systems is presented. Therefore, the state of the art in the field of data acquisition, processing and evaluation in manual assembly is discussed first. Then, process data are analysed based on the use case of terminal strip assembly. Here, the validation of the product data from 2021 is carried out by checking the data for normal distribution. This is followed by an analysis of the data with regard to the effects of spikes. Furthermore, the influences of a low data basis, different degrees of standardization and learning effects in the course of production are analysed. Finally, a discussion on the findings and further procedures will take place.

2. Process time acquisition in manual assembly systems

Manual assembly systems are often used where tasks change volatilely and a high adaptability to the changing circumstances is required. At the same time, due to this high flexibility, there is a challenge to be able to plan and control this type of work process efficiently with regard to productivity targets. [4, 5] In contrast to automated production, manual assembly systems are subject to a large number of influencing factors which have an impact on the assembly time as an important KPI. As illustrated in Figure 1, in addition to product and process properties as well as the design of the supplier network and the assembly system with its environmental conditions, primarily human factors influence the actual execution of the assembly task.

In the context of production planning, an assembly process is initially derived from the existing p*roduct properties* and the design of the manufacturing system. In relation to the product, its complexity should first be mentioned as an important factor influencing the process time. The authors Samy/ElMaraghy [8] define a significant correlation between increasing product complexity and increased assembly effort. The complexity measure described here depends, among other things, on the number and geometries of the components. Other important factors are the required tolerances and the type of product structure. [9] The *process properties* are directly dependent on the product properties. One of the most important influencing factors is the level of standardization [10, 11]. The manual processes are often found in SMEs. Especially in these companies with only a few employees, the workflows are less standardized and the workers often have a more diversified range of tasks. The lower the degree of standardization in the assembly system, the greater the possibilities for individual operations by the employees. This makes it more difficult to capture operating data accurately. Furthermore, the scope of the process and the process complexity are relevant factors [10, 11]. Within the context of assembly, this complexity results from energetic and informational activities. According to Schlick, assembly involves precise movements with low forces and can therefore be classified as a rather energetic task with an informational proportion. [12] In particular, the technological and content-related process diversity as well as the number of assembly operations are major complexity drivers [13]. In the category of *production system*, the number of workstations and their layout have a major influence [1, 13]. In this context, the differentiation between one-piece flow and batch production is also important [1]. Finally, the required equipment and supplies [13], as well as ergonomic aspects, are also significant.

Subsequently, the *environmental effects* of the assembly system are also relevant for the work being performed. These include first and foremost the fundamentals defined in DIN 6385 "Principles of ergonomics for the design of work systems" with regard to the aspects of temperature, light or even air purity.

[14] Also, the framework conditions related to *scheduling and network* aspects have an influence on the actual activity carried out. The order volume [10] and the order sequence need to be mentioned as well. Furthermore, delivery dates and the delivery reliability of suppliers in particular influence the work of the employees. This also includes the number of suppliers and the quality of the components [13].

In addition to these technical influencing factors, it is primarily the *human factors* that have an impact on the assembly processes actually carried out in manual production systems. In the context of this examination these are classified into the categories of qualification, learning, stress, fatigue, motivation and well-being. [10, 13] In addition to basic qualification [15], learning in production is a particularly important influencing factor [16, 17]. In the production environment, learning usually means a decrease in processing times and material consumption over time. This occurs due to repetitive work operations and the increasing experience of the employee as a result. This relationship was published by Wright as learning curve theory. Assuming unlimited time and a constant learning rate, it can be observed that the average cumulative value per product decreases by the same rate when the number of products is doubled. [16, 12] In line with current knowledge, this correlation has been adjusted so that an average learning curve for a batch can be characterized by processing times which initially decrease steeply and then more slowly as the number of units increases. Based on the non-constant learning rate, a level of saturation finally results. Such learning effects occur especially at the beginning of a batch, which is why they are of particular importance in the production of small batches [18]. Furthermore, the more complex the activity, the steeper the learning rate [19]. In addition to the learning effects, the aspects of stress and fatigue [10] as well as motivation and well-being also have an influence on the assembly time [20]. These aspects are based on the four levels of Maslow's pyramid of needs. This was further developed by Landau according to production-specific issues [20]. Thus, the activity should first be theoretically feasible. Based on this, Landau describes the tolerability that can be achieved by designing occupational safety according to the state of the art. Finally, an activity that can be performed on a permanent basis is expected to be reasonable. This third stage involves a human-oriented work design as well as a fulfilment of the employees' expectations. Finally, the goal of the fourth stage is to achieve a high level of satisfaction by ensuring the development of personality as well as social acceptance. [20, 21]

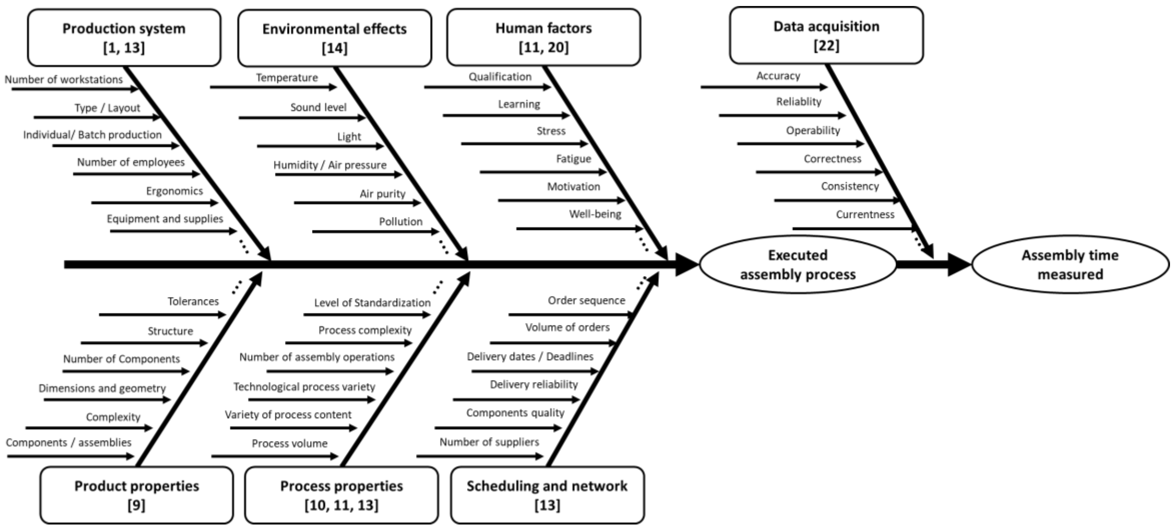

Figure 1: Factors of influence in manual assembly systems

Considering this complex relationship, it is not surprising that it can be seen in practice how the actual process deviates in principle from the specifications of the assembly planning. Even if the same target of assembly of two or more components is achieved, it is still an individual variation of the specified work process. [7] Therefore, real data from the assembly system are essential for efficient production control in terms of production data acquisition. From the diverse constraints in manual assembly, a high level of complexity can be derived for the design and implementation of a production data acquisition system (PDA).

This must consider the volatile activities as well as the fluctuating environmental conditions and at the same time must not disrupt the workflow or lead to increased secondary workloads. Still, it must be observed that no supervision of the employees takes place and at the same time an objective data basis is ensured. [4] Here, the principles of the data quality requirements defined by Fox, such as accuracy and reliability, must be considered [22]. Also due to these aspects, the most commonly used methods for capturing process times are the direct conversation with employees and the use of forms and reports by means of simple software tools [23]. In addition to self-recordings, multi-moment measurements and, time studies according to REFA continue to be the most common time determination methods in the industrial environment [24]. These are usually associated with a large initial effort as well as expenses in case of changes. The acquired data must then be processed. First, outliers and implausible values must be filtered out, and then a validity check must be performed. After Dekena, the box-plot method is suitable for filtering data in a production context [25].

In order to examine the validity of random variables with a continuous probability function, different tests are suitable. Common methods are the $\chi 2$-test, the KS test or the Cramér-von-Mises test. [26] The procedure includes first the choice of a suitable model. Furthermore, the parameters of the model are estimated on the basis of observations and graphical methods [26]. Thus, certain probability distributions can be inferred. In this case, the model of normally distributed random variables is of special importance [27]. The normal distribution is usually seen in populations and can be used to describe the random dispersion of measured values. Besides determinations in natural sciences and medicine, this unimodal distribution is often strongly asymmetric, especially in the context of mechanical engineering. The normal distribution is usually seen in populations and can be used to describe the random dispersion of measured values. Besides determinations in natural science, this unimodal distribution is often strongly asymmetric, especially in the context of mechanical engineering. In the case for positive, right skewed distributed data, the natural lognormal distribution is applied. Here, the higher frequencies are located on the left side. [28, 30] In manual assembly systems, many small random influences overlay each other multiplicatively. This leads to the assumption that, from a certain amount of data, a normal distribution can be observed in the process times. Furthermore, since each assembly task is subject to a strictly physiological limit, a right-skewed distribution is to be expected. This corresponds to a logarithmic distribution. Thus, a variable to be examined is log-normally distributed exactly when its logarithm is normally distributed [29]. For verifying the log-normal distribution, the data values are first logarithmised and then the normal distribution is tested [30].

In this context, the Kolmogoroff-Smirnoff test is used to examine the normal distribution. With this goodness-of-fit test, the empirical distribution function is compared with the theoretical normal distribution. The advantage of this test is the lower effort and a good result even in case of a small number of data values compared to the $\chi 2$-test [31]. This test can be used to check whether a random variable follows a previously assumed probability distribution [32]. In order to verify for normal distribution, the maximum perpendicular distance of the cumulative values is compared with a critical value. The calculation of the critical value depends on the significance level and number of samples [31]. In the literature, the significance level is often set between 0.01 and 0.1 [33]. It defines the range of rejection. When the sample is within this range, the null hypothesis of normal distribution is rejected. Accordingly, the smaller α is chosen, the greater the probability for the result of the investigation to define the data set as normally distributed [34].

3. Examination by means of the case study terminal strip assembly

The approach for validating and interpreting production data of manual assembly systems is explained below using the use case of terminal strip assembly of the Chair of Production Systems. First of all, it must be determined whether the use of the production data acquisition system has resulted in valid production data. This is the basis for using the data for the calculation of KPIs and production control. Furthermore, the data are examined regarding to the influencing factors. In addition to the expected log-normal distribution of the process values, this includes, the analysis of learning curves as well as malfunctions and measurement errors.

3.1 Experimental setup and test procedure

The terminal strip assembly can be assigned to the area of small parts assembly with a high diversity of variants. It is exemplary for other manual assembly processes in mechanical engineering. The assembly system is operated in cooperation between the Chair of Production Systems and the company Phoenix Contact GmbH & Co KG and represents an industrial environment with real orders. [35] The first step in the production of terminal strips is to cut the rails to length. These are then transferred to workstation 1, where the terminals are mounted on the rails. This is followed by the labelling at workstation 2, where small labels are applied. After that, the assembly of circuit bridges takes place at workstation 3. Subsequently, the desired functionality of the terminal strip is ensured by quality tests at workstation 4. Workstation 5 is used for pre-wiring the terminal strips. The final workstation 6 serves to package. [35] The assembly is carried out by two experienced employees who are supported by an assistant during peak loads. The process times of the assistant are not considered. The product portfolio of the terminal strip production comprises 70 variants, each consisting of a unique composition in terms of the number and variation of terminals, labels, circuit bridges and other components. In 2021, 31 of these variants were produced between 10 and 1173 times.

In the scope of this examination, the production period from 07.01.2021 to 03.12.2021 is considered. A total of 8799 terminal strips were produced, of which 5740 were recorded by the PDA. This results in an acquisition rate of 65.23%. The reasons for the non-recorded values of about one third of the products consist in the non-consideration of the process times of the assistant as well as in technical aspects during the introduction and smaller revision steps of the PDA. Ultimately, the familiarization of the employees with the new system, especially at the beginning, also meant for a lower acquisition rate. The processing times were recorded for each assembly part process using a tablet-based app. The processing times for every assembly station are recorded for each order and product. In addition to these productive times (operating state *production*), the pause times and non-productive times, such as setup, rework or malfunctions, were also recorded. In the period under review, 85% of the data relates to the operating state *production*, 10% to *pause* times and 3% to *setup*. The data volumes of the other operating states comprise less than 1%. The subsequent validation of the production data focuses on the *production* times of the terminal assembly, labelling and bridge assembly stations, since this is where the assembly activities take place. In this way, a total of 63% of the productive times of the assembly system are analysed.

With regard to the general conditions under which the investigations were carried out, it can be stated that the influencing factors shown in Figure 1 with regard to the categories of *process properties*, *production system* and *environmental effects* were constant during the period of investigation. The *product properties* are liable to the variance that is defined by the range of parts. In relation to the category *order planning and network*, the factors part quality and number of suppliers are fixed. In the course of real production, changes occur continuously with regard to order-specific aspects such as order sequence, order volume, deadlines and delivery reliability. The changes in these parameters can be considered in the analysis with the help of the PDA and digital order planning. The category of *human factors* is constant in terms of qualification. The parameters learning, stress, fatigue and motivation continue to fluctuate depending on the current boundary conditions and individual constitutions of the employees. These cannot be measured directly. However, conclusions can be drawn from the collected process data, so that indirect statements can be made about this during data analysis. Furthermore, the aspect of well-being cannot be measured with the used PDA system.

3.2 Presentation of results

Consequently, the processing times at the three stations are examined for validity on the basis of the 31 different terminal strip variants. For this purpose, the entire data set is first filtered using the box-plot method. Figure 2 initially shows that the variants were produced in varying numbers and frequencies in 2021. Furthermore, there is an data acquisition rate for each variant. The terminal strip variants are sorted in ascending order with regard to their assembly complexity. The complexity depends primarily on the number of different components, the total number of components and their properties. [36] A more complex variant tends to be more complex to assemble, which is also reflected in the processing times. The average processing times per station is 201 s for terminal strip assembly (labelling: 202 s, bridge assembly: 114 s).

	Terminal strip variant	1118657-00	1251392-00	8195464-00	51001479	51022259-00	1027086-00	51006560-00	1022246-00	51000454	1057228-00	1003593-01	1118659-00	1003605-02	1003596-01	1065435-01	8195786-03	1033667-00	1003594-01	8196268-03	1014685-01	51028268	1029463-01	8190711-01	8199999-01	8197399-03	8196946-01	8197501-03	1027348-00	1021640-03	1107854-00	8197398-03
Order data	No. of products produced in 2021	220	13	125	370	250	2600	1100	50	350	14	40	400	40	40	10	75	436	55	10	80	150	99	460	20	529	10	10	30	629	40	544
	Average Batch Size	37	13	21	123	83	867	550	10	117	5	6	57	6	6	10	25	27	6	10	27	19	10	38	10	21	10	10	15	20	20	23
	Production data acquisition rate	91%	77%	100%	65%	100%	45%	36%	100%	43%	93%	88%	81%	88%	88%	100%	100%	92%	82%	100%	75%	69%	78%	83%	100%	87%	100%	100%	70%	93%	50%	76%
	Product complexity	4,62	4,64	4,80	4,81	4,82	4,83	4,92	4,94	5,03	5,53	5,59	5,67	5,69	5,79	6,01	6,09	6,14	6,17	6,24	6,27	6,35	6,35	6,40	6,41	6,44	6,57	6,61	6,61	6,62	6,72	6,78
Station 1	Median1	32	34	43	110	53	76	40	49	90	57	263	49	482	467	147	188	282	271	352	162	232	165	166	187	469	316	197	279	284		499,2
	Standard deviation1	0,27	0,16	0,18	0,30	0,24	0,29	0,23	0,21	0,26	0,11	0,12	0,17	0,19	0,30	0,08	0,25	0,16	0,21	0,39	0,26	0,54	0,29	0,17	0,10	0,19	0,10	0,08	0,27	0,23		0,286
	Log-normal distributed?	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No		No
Station 2	Median2	43	21	21	34	29		31	31	63	14	392	88	628	577	76	312	178	197	277	237	118	225	247	312	234	166	347	366	117	309	365
	Standard deviation2	0,20	0,14	0,29	0,14	0,20		0,16	0,43	0,14	0,16	0,15	0,37	0,16	0,12	0,11	0,94	0,10	0,15	0,13	0,11	0,33	0,19	0,16	0,06	0,13	0,10	0,11	0,06	0,17	0,32	0,14
	Log-normal distributed?	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Station 3	Median3		13	6							12	96	37	68	157	43	248		388			80	103				326			114	12	
	Standard deviation3		0,14	0,00							0,22	0,16	0,15	0,32	0,24	0,15	0,15		0,24			0,32	0,26				0,10			0,17	0,20	
	Log-normal distributed?		Yes	Yes							Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes			Yes	Yes				Yes			Yes	Yes	

Figure 2: Evaluation results

As shown in Figure 2, the procedure for validating process data of manual assembly systems described in Chapter 2 results in a normal distribution rate of 90% for the terminal assembly station. Out of the 30 variants considered here, the distributions of the recorded assembly times of 27 variants are log-normally distributed. A similarly high rate of 93% was obtained for the station labelling. Here, sufficient data were also collected for 30 variants to check the normal distribution. Thus, 2 variants are not log-normally distributed. The third assembly station, bridge assembly, in contrast, has significantly less data. Here, all recorded production times are log-normally distributed.

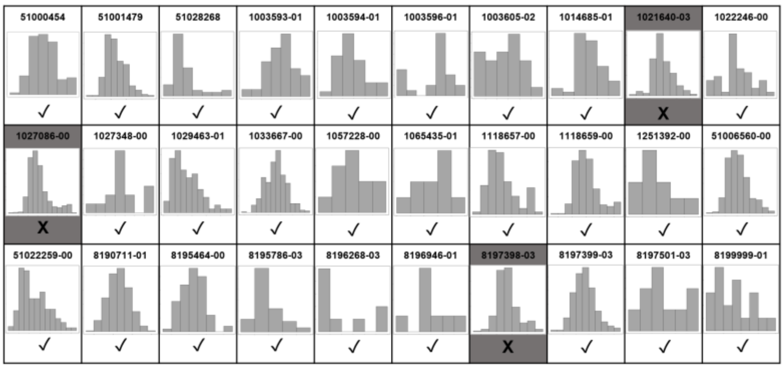

Figure 3: Processing time histograms of terminal assembly (**x** - not log-normal distributed)

3.3 Evaluation and discussion

When taking a closer look at the individual histograms, a bell-shaped or right-skewed, logarithmic distribution can often be seen (see Figure 3). This pattern of the distributions allows the conclusion that it is valid process data. Furthermore, conclusions can be drawn about the production process and the data acquisition method. The frequently observed right-skewed distributions of the process values are shown as an example in Figure 4 using the histogram for the data of variant 8197399-03 of the station labelling. In relation to this variant, 529 products were produced in the period under review with an average batch size of 21 pieces. The acquisition rate is 87% and the median processing time is 234 seconds. The exemplary distribution of the measured values, which is characteristic for the majority of the data, can be distinguished on the basis of three different areas. It should be noted that these areas are not subject to a strict separation, but rather a flowing transition.

The *first area* contains the lowest values up to 200 seconds. Here, a strong increase in frequency can be seen. In connection with the median of 234 seconds, this leads to the conclusion that the majority of the values in this area must be the result of technical measurement errors or incorrect usage of the PDA, since a processing time lower than 200 seconds is not achievable even for a skilled worker. This "physiological limit" can thus be seen in the majority of the histograms. In contrast, realistic values can be assumed in the *second area*. This area contains the majority of the recorded values and always includes the median of the processing time. Nevertheless, there is also a scattering of values between 200 and 260 seconds. This can be interpreted as normal performance fluctuation in manual assembly. In this example, the *third area* of the histogram contains all process values from 260 seconds and includes significantly fewer data values compared to the second area. For the majority of the recorded distributions, a staircase-like decrease in the frequencies with increasing processing time can be seen here. This is probably due to disruptions in the production process and problems with the assembly task. However, data resulting from incorrect operations can also be found here. Another reason for increased process times in this area can be learning effects. In the context of this variant with a high production frequency, this means a rather small influence.

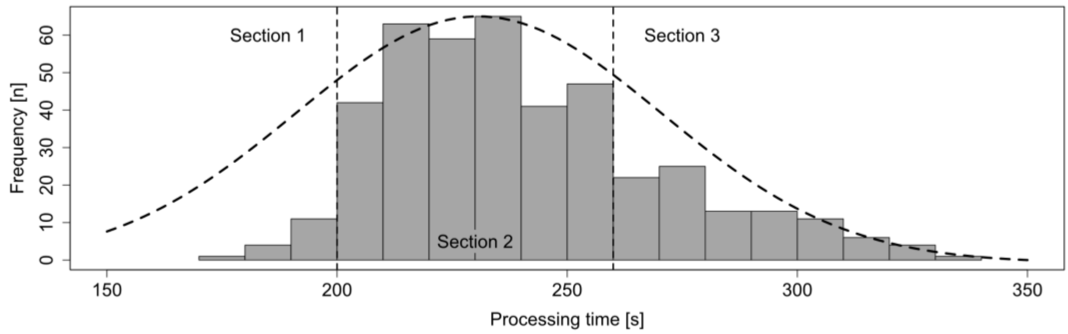

Figure 4: Histogram of the processing times of the terminal strip variant 8197399-03 at the labelling station

In contrast to this example, five data records do not correspond to the log-normal distribution. A closer look at the measured values shows specific reasons, which will be discussed in the following using the four categories *incorrect usage of the PDA, average processing time, lack of standardization* and *low data basis*.

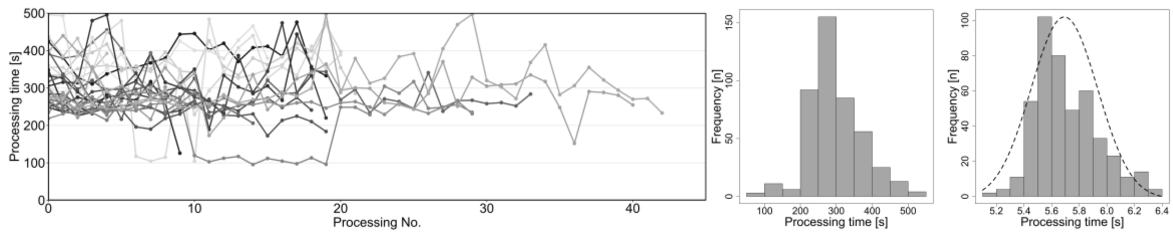

Figure 5: Terminal assembly of variant 1021640-03: a) Production order processing times; b) Histogram; c) Log-normal distribution

First of all, as with the explanation of the measured values from the first and third area, the *incorrect usage of the PDA* should be mentioned as a source of error. This can be seen particularly in the example of variant 1021640-03 (see Figure 5). The main reason for the non-existent log-normal distribution here is the process data of a few orders. This becomes clear when looking at Figure 5. Here, all 31 completed jobs of this terminal strip variant at the terminal assembly station are plotted. As also shown in the histogram, the majority of the measured values are in the range of 200 to 400 seconds. The median is 284 seconds. However, there are also 2 jobs with many physiologically unrealistic values below 200 seconds and a large number of process values above 400 seconds. In total, this means that no log-normal distribution prevails here.

The second category is the *average processing time* of the assembly activity. This is particularly evident in the example of the labelling of the terminal strip variant 102640-03 (see Figure 6). Here, the median of the processing time amounts 117 seconds. Basically, the histogram shows a similar distribution to the example in Figure 5. Nevertheless, the difference here is the significantly shorter processing time, which means that disruptions in the operating sequence and operating errors have a greater influence. With long processing times of several minutes per product, these are less significant than with such short processing times.

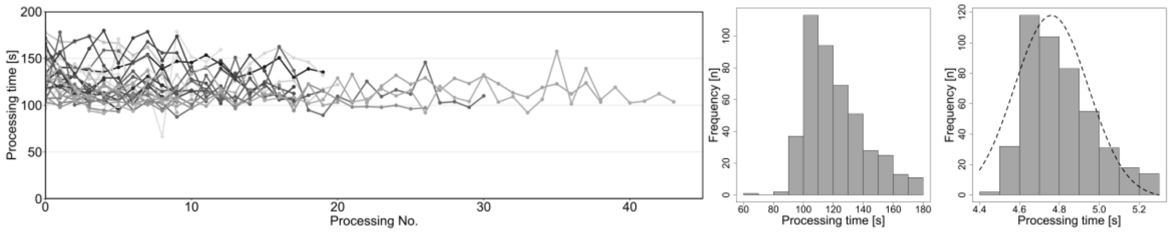

Figure 6: Labelling of 1021640-03: a) Production order processing times; b) Histogram; c) Log-normal distribution

The third category includes the error source of *lack of standardization* (see Chapter 2), which can be seen in particular in the example of the assembly of terminal strip variant 8195786-03. Figure 7 shows that two out of three production orders recorded have a clearly different average processing time. The difference in the processing time corresponds approximately to the duration of the processing time for bridge assembly. In both cases, no data is given for the bridge assembly, which leads to the conclusion that the employees have assembled the bridges already at station 2. This correlation is noticeable because of the few orders with little data, so that the box plot filtering does not apply.

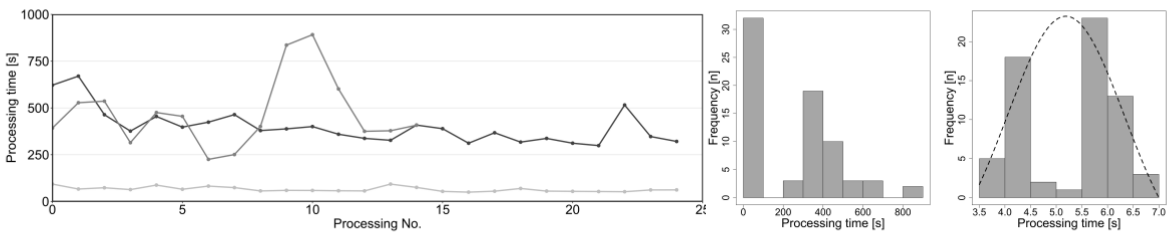

Figure 7: Labelling of 8195786-03: a) Production order processing times; b) Histogram; c) Log-normal distribution

The fourth category includes this context of a *low data basis*. The terminal assembly of variant 1027086 is selected here as the example (see Figure 8). Here there are three different orders with an average batch size of 867. The median processing time is 76 seconds. An examination of the histogram shows that the malfunctions and failures are much more significant here than in the case of more complex variants. Another reason for the larger number of high process values could also be a learning effect, since this variant was only ordered three times.

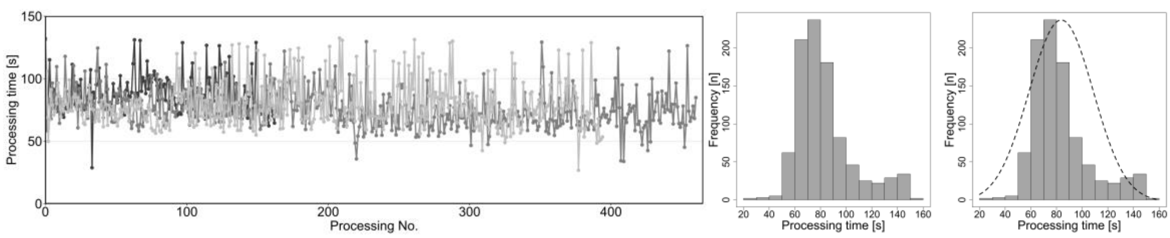

Figure 8: Terminal assembly of variant 1027086: a) Processing times of the individual production orders; b) Histogram; c) Log-normal distribution

For further investigation of possible learning effects, an exponential regression line was calculated for the respective data of the production orders. If the algebraic sign of the gradient is negative for these functions, it can initially be concluded that there has been an average improvement in processing times in relation to the individual products of a batch. Thus, in 75% of the 465 production orders examined, a reduction in the processing time per product can be observed in the course of the work progress. This can be differentiated in relation to the individual stations. This shows that 68% of the orders for terminal assembly have a reduced assembly time in the course of processing (78% for labelling, 86% for bridge assembly). There may be various reasons for this. According to Buck, in addition to the learning effect, changed work processes can be mentioned here, for example. Thus, learning effects cannot be proven here, but only disproved. [37]

4. Conclusion and Outlook

In summary, it can be stated that the data acquired in the field of terminal block assembly can be considered as valid. This becomes particularly clear when looking at the distribution of frequencies in detail. This finding is an absolute basis for further analysis of the data set with regard to the influencing factors in manual assembly described above. This paper already provides important approaches for this. In addition to the identification of a physiological limit of the processing time, it could be shown that the influence of malfunctions in the operating process as well as incorrect operations increases with decreasing processing time. Finally, it was also shown by means of an example that a high degree of standardization is absolutely necessary in order to be able to calculate useful key figures on the basis of valid data. Furthermore, a small data basis means that the box plot method is less suitable for filtering the process values. When looking at the individual assembly orders, it has also become clear that a decreasing processing time per product with increasing work progress can be observed for the majority of the assembly lots recorded. This leads to the suggestion that there may be some form of learning. Here, a further assumption is that this effect occurs more strongly with increasing product complexity as well as with increasing batch size. In addition to this aspect, the influence of pause times and the influence of delivery deadlines will be the subject of further investigations. However, due to the complex correlations between the influencing factors, often only assumptions can be made. For a more precise analysis of the causes of human factors and for the creation of effect models, extended PDA systems and systematic experiments are required. The aim is also to vary and investigate influencing factors that were still set as fixed in the present use case. These include, among other things, the involvement of additional employees, the variation of the order sequence, and the modification of the process sequences, for example with regard to batch or piece production.

Acknowledgement

This research and development project is founded by the German Federal Ministry of Education and Research within the “SME – Innovative: Research for Production” Funding Action and implemented by the Project Management Agency Karlsruhe. The author is responsible for the content of this publication.

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