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REASONING: INSTALLATION PROCESS STEP INSTRUCTIONS AS AN AUTOMATED ASSEMBLY TIME ESTIMATION TOOL

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ABSTRACT

Assembly time estimation is an important aspect of mechanical design and is important for many users throughout the life-cycle of a product. Many of the current assembly time estimation tools require information which is not available until the product is in the production phase. Furthermore, these tools often require subjective inputs which limit the degree of automation provided by the method. The assembly of a vehicle depends on information about the product and information describing the process. The research presented in this paper explains the development and testing of an assembly time estimation method that uses process language as the input for the analysis.

Keywords: Process Sheets, Automotive, Assembly, Time Estimation

1 ASSEMBLY TIME ESTIMATION

Manufacturing enterprises are competing in increasingly competitive global markets, requiring them to compete in terms of quality, cost, and time to market of their products[1-3]. In order to operate efficiently and competitively these firms must understand the costs associated with the manufacture of their products[3]. It is increasingly important for this understanding to be developed earlier in the life-cycle of a product. It has been shown that the design phase often defines up to 80% of the costs of a product while the phase itself only consumes less than 15% of the budget[4-6].

Assembly time estimation has been shown to help everyone including managers, workers, and consumers in four ways[7]. Assembly time estimation assists methods improvement, the process of making assembly tasks more efficient, thus reducing the cost to produce. Secondly, assembly time estimation allows for a standard of performance that allows for rational management of operations. Third, a consistent standard of measurement allows manufacturers to reward exceptional performance resulting in reduced labor costs and improved employee pay. Lastly, the cost of the product to the consumer is reduced while the employer is more competitive in the marketplace and the employee's job is protected[7].

Efficiency has become an important focus with the evolution of the Ford manufacturing system and the Toyota Production System in the 1950's concentrating efforts on eliminating waste. This focus led to the development of lean manufacturing, resulting in an emphasis on eliminating waste while increasing production and quality[8]. This trend also required the development and standardization of assembly time estimation methods.

Assembly time estimation is used by designers, process planners, line balancing personnel, ergonomics analysts and others. Designers use this information to evaluate between different designs and to improve their designs in terms of assembly. Process planners and line balancing personnel use this information to efficiently lay out the assembly line. Ergonomics analysts use this information to understand the ergonomic implications of specific assembly tasks. Assembly time estimates can be used more effectively if it is available earlier.

Current assembly time estimates often require information about how parts are to be handled and inserted into an assembly. Unfortunately, this information is often not available until later in the product life-cycle. For this reason, other means of estimating assembly times must be explored to provide assembly time estimates earlier in the product life-cycle.

The assembly of a product depends on information about the process and information about the product. As a product moves further along in the development life-cycle, more information is available about the product and the assembly process. Furthermore, the available information increases in certitude as the process is furthered. It is expected that as more information becomes available assembly time estimates can be more accurate. Figure 1 shows a portion of the automotive development timeline. The right end of the timeline represents the point at which the vehicle goes into production. Generally, a prototype build is performed several months prior to the start of full scale production. This is likely the first chance for existing time studies to be performed. Pre-launch assembly plans are available well before the prototype build. At this point the process instructions describing how the vehicle is to be assembled are available. Therefore, assembly time estimation based on process instructions can be performed at this time, often 16 or more months prior to production.

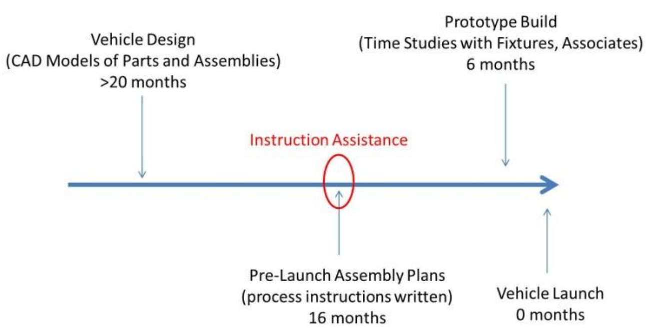


Figure 1: Automotive development timeline

The goal of this research is to explore the ability of process language to be used as an input for assembly time estimates. Assembly time estimates made at early stages of a product life-cycle are not expected to be as accurate as those which are conducted during production because there is substantially less information available at this stage. Therefore, the estimates sought in this research are not intended to replace full scale assembly time studies which take place during production, but to supplement them by providing information about assembly time earlier in the product life cycle.

2 INSTALLATION PROCESS INSTRUCTIONS

Process instructions are intended to explain specific assembly processes to the associates who assembly vehicles. These instructions are often available sixteen or more months prior to the start of full-scale production.

2.1. Origin of Process Instructions

Process instructions in the automotive industry are generally authored prior to the start of production, but after the completion of most of the design work[9]. At this stage of the product life-cycle, other assembly time estimation techniques are not able to be performed because they often require information about how parts are to be handled and inserted into assemblies and this information is not yet available. Process instructions are required to plan the assembly process so no additional effort is required to obtain this information. This is another benefit of developing an assembly time estimation tool that uses process language as input for the analysis.

2.2. Composition of Process Instructions

Process instructions usually include a verb, an object or part, and a number of objects or parts. This is often followed by a phrase that further describes the process. This may describe where the part is to be installed or what tool is to be used. Variation between process instructions is likely due to different authors and different areas of the vehicles being described. This variation must be considered when evaluating the results of an assembly time estimation method based on inputs from process instructions.

It is likely that the three most semantically important aspects of the process instruction are the verb, the object or part, and the quantity of objects. These three components should allow for a basic understanding of the assembly task to be performed. These components of the instruction tell what action should be performed, what the action is to be performed on, and finally the number of times the action is to be performed. A few examples of process instructions from an automotive manufacturer are shown in Table 1. The values in parenthesis represent a quantity that is not explicitly stated in the process instruction. In this case, the default quantity is one.

Table 1: Examples of process instructions

Instruction	Verb	Qty.	Object	Remainder
1	Retrieve	(1)	Harness	From line side parts rack
2	Position	(1)	Harness	Into channel
3	Tighten	2	Screws	-

For the purposes of the research presented in this paper, the components of the process instructions that are analyzed include verb, quantity, object, and volume of object. The process instructions used in this research were collected from one automotive assembly plant and include processes from nine different vehicle areas. Furthermore, process instructions used in the analysis were written by ten different process planners. A summary describing the process sheets used in the analysis is shown in Table 2. The process instructions were collected from different authors and vehicle areas so that the analysis is not based on a specific authoring style or area of the vehicle. In the next, section, the specific combinations of inputs used in the analysis will be addressed.

Table 2: Process instruction collection information

Vehicle Areas	Process Planners 1	2	3	4	5	6	7	8	9	10
Instrument Panel	55	0	0	0	0	0	0	0	0	0
Insulating Panel	0	4	20	0	0	0	0	0	0	0
External Fittings	0	0	0	15	0	0	0	0	0	0
Trim/mats	0	0	20	0	0	0	0	0	0	0
Rear Light Cluster	0	0	0	0	23	0	0	0	0	0
Test Electrics	0	0	0	0	0	1	1	0	0	0
Process Supply	0	0	0	0	0	0	0	3	4	0
Assembly Processes	0	1	0	0	8	0	0	0	0	0
Doors	0	0	0	0	0	0	0	0	0	68

3 LINEAR REGRESSION ANALYSIS

The first study performed to determine the ability of process instructions to be mapped to assembly times is a linear regression analysis. This analysis is focused on determining an assembly time that best represents the time to perform a specific action represented by a verb.

At a minimum, a work instruction can be written as an action verb followed by a phrase as shown in the two examples below.

"Align the two tabs on the bottom of the hood insulation to the slots in the hood."
"Insert a push pin to hold the insulation."

It should be noted that the interest is placed on the main action verb of the phrase and not the additional verbs which may be located inside prepositional phrases.

The analysis described in this paper considers 223 process sheets which include 665 process instructions. Each of the instruction considered in the analysis was written, or could be written as an action verb followed by a descriptive phrase. An example of how some of the process instructions were re-written for the analysis is shown below.

Original: "Using tool X, fasten part A to part B."
Re-write: "Fasten part A to part B using tool X."

A standard format allows for easier authorship of process instructions and permits the automation of process based assembly time estimates.

3.1. Verb List

The first step in the analysis is to identify an appropriate and adequate set of verbs to be used in the analysis. Two steps are performed to identify this set. First, a stability analysis is performed to determine the degree to which the verb list grows as each new process sheet is analyzed. The relationship between the number of process sheets analyzed and the number of distinct verbs discovered is shown in Figure 2.

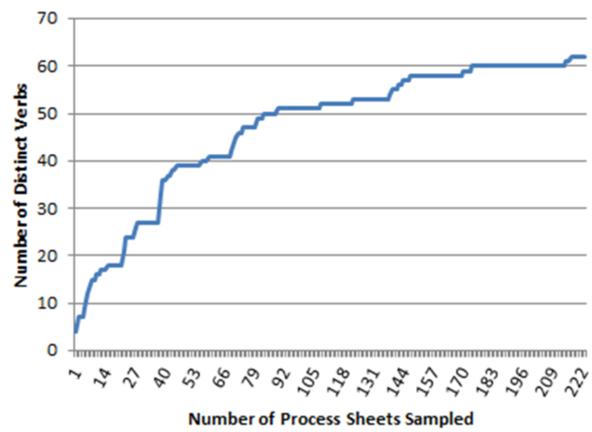


Figure 2: Relationship between process sheets sampled and verbs identified

Secondly, the master verb list shall be reduced to exclude repetitive and non-value added verbs. It is critical to prevent excluding verbs that are similar yet suggest additional information to users. As an example, "clip" and "fasten" are synonyms, however, clip can be a more descriptive verb than fasten as it explains how to fasten. Therefore, there is a tradeoff between having a minimum set of verbs, allowing for maximum repetition in the analysis and having a large set of verbs with little repetition. For these reasons, the pruning of the verb list must be done carefully and with these considerations in mind. The preliminary reduced verb set is shown in Table 3.

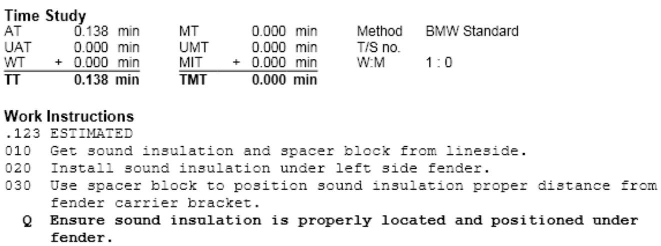
Table 3: Verb set used for process instruction analysis

Align	Disconnect	Install	Pull	Rotate	Tuck
Apply	Ensure	Loosen	Push	Scan	Turn
Assemble	Fasten	Maneuver	Put	Seat	Unplug
Attach	Feed	Move	Read	Secure	Use
Bring	Fix	Open	Receive	Set	Verify
Check	Flip	Operate	Release	Slide	Walk
Clean	Get	Pick	Remove	Snap	Write
Close	Guide	Place	Re-open	Start	
Compare	Hand	Position	Restock	Take	
Confirm	Hand Start	Prep	Retrieve	Tear off	
Connect	Insert	Press	Return	Tighten	

This current master verb list is being refined through interviews with process planners, through a top-down approach in examining the verbs used in time analysis worksheets at the automotive OEM, through linguistic analysis of parts of speech patterns and synonym analysis, and through statistical analysis on larger sets of instruction worksheets. This paper presents the preliminary results and the direction of investigation that demonstrates the promise associated with this approach.

3.2. Analysis

After a standard reduced set of verbs has been identified and the formatting of work instructions allows for easy identification of the verb, the analysis can be performed. In the analysis, the time study estimates as provided by time study personnel analyzing the process on the line are used as targets. The linear regression analysis uses an average time associated with each occurrence of the verb in the observed process instructions assuming an equal share of time for each verb in the process sheet. Figure 3 provides an example of a process sheet.



Time Study

AT	0.138 min	MT	0.000 min	Method	BMW Standard
UAT	0.000 min	UMT	0.000 min	T/S no.	
WT	+ 0.000 min	MIT	+ 0.000 min	W:M	1 : 0
TT	**0.138 min**	**TMT**	**0.000 min**		

Work Instructions

```
.123 ESTIMATED
010  Get sound insulation and spacer block from lineside.
020  Install sound insulation under left side fender.
030  Use spacer block to position sound insulation proper distance from
     fender carrier bracket.
  Q  Ensure sound insulation is properly located and positioned under
     fender.
```

Figure 3: Process sheet example

The verbs associated with the process sheet shown in Figure 3 include Get, Install, and Position. The quality checks, shown in bold in Figure 3, generally consist of a brief glance to determine whether a part is in place or connected properly. Due to their brevity and unsubstantial portion of the total process time, quality checks are not considered in this analysis. The target assembly time estimate is shown as 0.138 minutes. Therefore each of the 3 action verbs is associated with .138/3 or .046 minutes. This process is repeated for 200 process sheets. The average time associated with each verb is considered the estimated time for each of the verbs in the list.

After each of the process sheets have been analyzed and appropriate times have been determined for each of the verbs, the results are tested both internally and externally. During internal validation, the model is tested against process sheets that were used in the analysis. The external validation consists of testing the model against process sheets that were not a part of the training set. The internal validation shows errors in the range of -87 to +138 percent. The external validation resulted in errors ranging from -53% to 850%.

The results of the analysis show that a linear regression style analysis is not sufficient for the desired mapping. However, artificial neural networks are good at pattern classification and recognition and are able to learn from experience[10]. Artificial neural networks work best for problems in which the solutions require knowledge that is difficult to specify but there exists a significant amount of observations[10]. Due to the vast number of process sheets which can be used to train a neural network, this type of analysis is employed in the next section.

4 ARTIFICIAL NEURAL NETWORK ESTIMATION TOOL

Artificial neural networks (ANN) have been shown to be useful in estimating assembly time [11], product market costs based on function structures [12, 13], and project team performance metrics [14, 15] when using structural complexity metrics. This section explores the potential to use ANNs in linguistic analysis of installation instructions for predicting assembly time.

Two of the important factors for artificial neural network analysis are the inputs and the targets. The information used in the analysis presented here is collected from existing process sheets. The targets used in the analysis are the results of formal time studies. These estimates are the result of a formal study performed by time study personnel. The studies are conducted using a company specific adaptation of MTM-UAS. The goal of this study is not to replace these formal time studies, but to provide information much earlier in the product life-cycle. The existing time studies occur after the vehicle has entered production and take up to an hour per process sheet.

The inputs for this analysis are different combinations of process instruction components. The components that were considered include the verb, object, number of objects, and volume of objects.

4.1. Initial ANN Results

The next step in performing analysis with artificial neural networks is determining the most appropriate architecture. One hundred eighty-nine different artificial neural network structures are simulated in order to identify the most appropriate for this application. The neural network architectures examined consist of one to three layers. Single layer architectures include a neuron count of one to fifteen. Architectures with two layers were used with neuron configurations ranging from one neuron each up to seven neurons in each layer. Finally, architectures with three layers were explored with neuron counts of up to five neurons in each layer.

The original analysis was performed using a training of 93 process instructions and their respective time study results as targets. The input data from the process instructions included the following combinations of verb, object and number of objects: (verb, object, and quantity), (verb and object), (verb and quantity), and (verb). After the neural network has been trained, the performance of the architectures is evaluated using 21 process sheets that were not included in the training. The neural network is simulated using these 21 inputs and the estimated times for each set of process sheets is determined.

The neural network is then simulated 100 times for each set of inputs resulting in 100 simulated assembly times for each input set. Next, the performance of each of the architectures is determined by calculating the percentage of the twenty-one test cases in which the estimated time is within 100% of the target assembly time. The results of this analysis for the top performing architectures are shown in Table 4. The percentages in this table represent the confidence that a simulated assembly time value will be within 100% of the target time.

Table 4: Results from original ANN training

Architecture	Verb + Object + Quantity	Verb + Object	Verb + Quantity	Verb
9 - [9]	95.24%	76.19%	4.76%	19.05%
20 – [1,5]	90.48%	4.76%	42.86%	4.76%
27 – [2,5]	66.67%	66.67%	14.29%	14.29%
61 – [7,4]	4.76%	23.81%	42.86%	9.52%
91 – [2,1,2]	85.71%	9.52%	47.62%	23.81%
151 – [4,3,2]	23.81%	9.52%	33.33%	19.05%

The best results are obtained when an artificial neural network architecture of one layer with nine neurons is used and the input vector contains the verb, object, and quantity. When this setup is used, roughly 95% of the test cases are estimated to within 100% (-100% to +100%) of the target assembly time. Table 5 shows the results using these inputs and architecture #9 for four test cases.

Table 5: Results of initial artificial neural network analysis

Test Case	Target Time (min)	Predicted Time (min)	Error
1	.224	.221	-1.3%
7	.081	.049	-39.5%
14	.078	.001	-98.7%
20	.069	.049	-29.0%

The probability density graph for one of the 21 test cases is shown in Figure 4. For each of these test cases, the inputs represent the verb, object, and quantity of objects, and the architecture used is a one layer network with nine neurons. In the figure, the target value is shown by the red dotted line while the mean predicted value is shown by the black dotted line. The x-axis range in the figure includes all values within 100% of the target value.

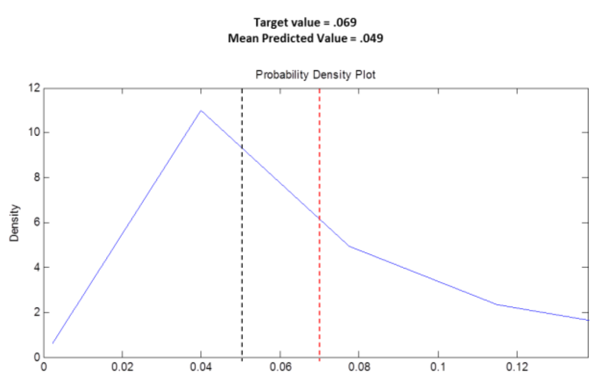


Figure 4: Test # 20, Architecture 9, Inputs=[verb, object, quantity]

The results displayed in Table 4 and Figure 4 show that the estimated times are not as accurate as expected. Two reasons are presented for this observation. First, the data set is relatively small considering the number of verbs and objects that are used to describe vehicle assembly. A relatively small number of repetitions of verbs and objects are available to be used in the artificial neural network training with the small training set. Due to the high number of objects particularly, a significantly higher number of process instructions must be analyzed to obtain a representative sample. It is suggested in statistics that sample size be based on a minimum subject-to-variables ratio of five to ten [16]. This would suggest that a minimum number of samples be large enough to contain five to ten repetitions of each variable. A histogram showing the repetitions of each of the distinct verbs in the analysis is shown below in Figure 5. The black dotted line in the figure represents the number of repetitions of each verb that would be required to meet the recommendation of ten repetitions of each variable. If the performed sampling is representative, 1,115 process sheets must be analyzed to reach the minimum recommendation of five repetitions of each variable.

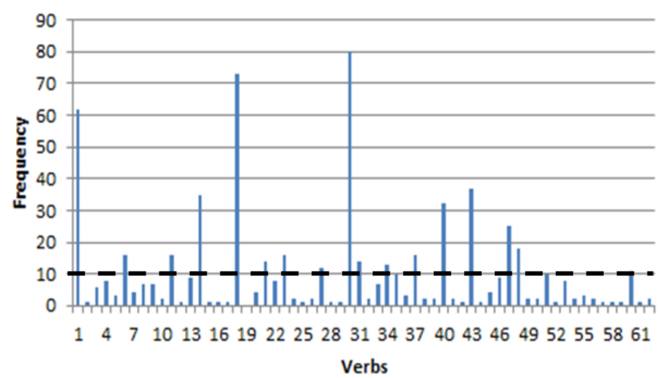


Figure 5: Histogram of verb frequency

Sample size is not the only issue that may lead to inaccurate results. It is important to consider the high number of different terms for objects which are similar and are roughly the same in terms of assembly difficulty. The analysis should be based on some characteristic of the object, not simply its name. It is suggested that the volume of the object is one of the primary drivers of assembly difficulty. The next section is a presentation of the analysis with volume used in place of object. Other characteristics to consider may include mass, type of assembly required, and bulkiness. The volume of an object is relatively easy to obtain and contains some degree of information representing other characteristics such as bulkiness and mass. For this reason volume is the first characteristic explored to determine its applicability to the model.

4.2. ANN Results Using Volume in Place of Object

In order to refine the analysis, volume is used in place of object. This serves two purposes. First, by using four volume classes, more repetition is introduces into the input data set. The four general volume classes include golf ball sized items, baseball sized items, basketball size items and finally suitcase sized items. Secondly, volume provides some additional information about the object that affects the difficulty of performing the task and likely the assembly time. Other assembly time estimation techniques penalize parts for small and large volumes[5]. Volume also often trends with mass and bulkiness, two additional factors that affect how difficult parts are to assemble. A more refined volumetric delineation may be possible with integration to CAD modeling systems, but is out of scope for this research.

4.2.1. Results with Fifty Input Samples

The first analysis using verb and volume as inputs for each process step consisted of 50 inputs and targets. The neural network was then simulated on 23 test cases that were held out of the training set. The size of the test case set is held constant for training sizes of 50 through 200; it is approximately 10% of the maximum training size studied. Table 6 shows the best performing neural network architectures as well as their associated probabilities of predicting assembly times to within 100%. The values in the right column of Table 6 are the percentage of the 23 test cases in which the mean predicted assembly time is within 100% of the target assembly time.

Table 6: Results with 50 training data points

Architecture	Probability of estimation to within 100%
122 – [3,2,3]	.6957
8 – [8]	.6521
101 – [2,3,2]	.6087
55 – [6,5]	.5652
154 – [4,3,5]	.5652

The best performing architecture is identified as one with three layers with three, two, and three neurons in each layer respectively. However, this architecture only results in a confidence of prediction of the assembly time to within 100% of the target time. This is likely due to the small set of input data points used in the training. The results of five of the test cases are shown in Table 7.

Table 7: Results of ANN prediction with verb and volume as inputs and 50 training points

Test Case	Target Time (min)	Predicted Time (min)	Error
4	.13	.12	-8%
8	.048	.278	479%
12	.054	.247	357%
16	.207	.061	-71%
20	.021	.183	771%

The results presented in this section show that to some degree process instructions, specifically the verb and volume can be mapped to assembly times. However, this mapping lacks accuracy due in part to the minimal number of data points in which the neural network has been trained on thus far. In order to more fully understand the ability of neural networks to map the verb and volume of a set of process instructions to an assembly time, the neural network training must be completed with a much higher number of data points. Figure 6 shows that if the accuracy trend continues to increase linearly, 350 data points would be required to raise to 90% the confidence level of prediction to within 100%. An analysis exploring the effect of training size on performance is presented in the next section.

4.2.2. Improvement with Additional Input Samples

The effect of sample size on the accuracy of assembly time estimation is examined in this section. For the analysis presented here, the test points are held constant, while the number of process sheets used to train the neural network is increased. Next, the top performing architectures as identified are evaluated.

Figure 6 shows the performance trend, representing the confidence of prediction to within 100%, of five neural network architectures as the number of data points used in the training increases from 50 to 200. A developing upward trend is shown by the orange dotted line. This line represents the average performance of the five architectures. It should be noted that 200 data points is still a small data set for artificial neural network training. However, the average performance of the neural network architectures trends from 62% to 75%. This trend suggests improvement, but should be validated with a nearly tenfold increase in the number of training points.

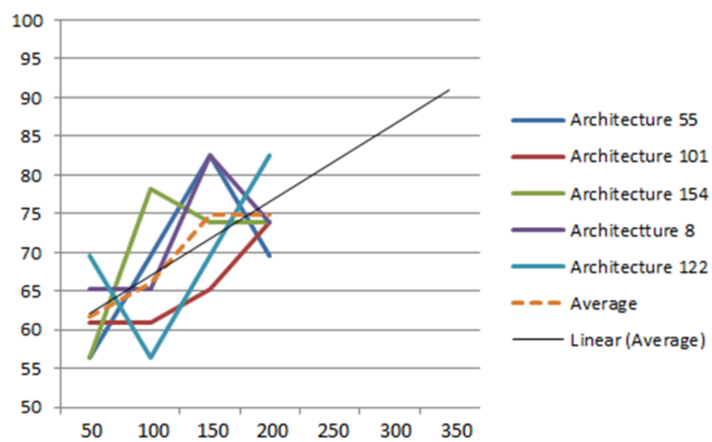


Figure 6: Architecture performance as a function of training size

The results of architecture 122 after training on 50 data points were shown. After training of the neural network using 200 data points, architecture 122 is again evaluated to determine its ability to predict assembly times.

Tab. 8: Results of ANN prediction with verb and volume as inputs and 200 training points

Test Case	Target Time (min)	Predicted Time (min)	Error
4	.13	.220	69%
8	.048	.076	58%
12	.054	.092	70%
16	.207	.447	116%
20	.021	.240	1043%

While some improvement is shown as more data points are used to train the neural network, the accuracy is still limited and inconsistent. However, the optimal neural network architecture has not been identified after 200 data points were used for the training. It is likely that after adding an additional 150 training points, a different architecture may be better suited for the mapping. The identification of the best architecture with 200 training points and the resulting accuracies in then presented.

4.2.3. Results with 200 Input Samples and Best Architectures

The process of identifying the most promising artificial neural network architectures is performed in the same manner as discussed above. The results of the artificial neural network training and simulation on the test data are collected and analyzed. The test data consisted of the same 23 data points used to identify the most appropriate architecture after training on only fifty points.

Table 9 shows the probabilities of estimation to within 100% and 50% of the target time for the top performing architectures. The probabilities greater than one are a result of errors in the integration approximation. These values can be taken to be a 100% likelihood that prediction is within the 100% of target range.

Table 9: Results with 200 training data points

Architecture	Probability of Estimation to within 100%	Probability of Estimation to within 50%
182 – [5,4,3]	1.05	.34
136 – [3,5,2]	.90	.40
17 – [1,2]	.84	.50
161 – [4,5,2]	.83	.46

The results of the analysis with the top performing architecture are shown in Table 10. With 200 process sheets used in the training set and the top performing artificial neural network architecture selected, the average error is 80%. While these accuracies are not ideal, it is shown that they continue to improve as more information is used in the training.

Table 10: Results ANN prediction with verb and volume as inputs and 200 training points

Test Case	Target Time (min)	Predicted Time (min)	Error
4	.13	.17	31%
8	.048	.02	-58%
12	.054	.044	-19%
16	.207	.105	-49%
20	.021	.072	243%

These test cases show promise but are not yet capable of providing a reliable prediction of assembly time. The next section provides a summary of the results and a discussion on how they can be used in future research.

5 CONCLUSIONS AND INFERENCES

The analysis as performed and presented in this paper does not provide for a conclusive estimation of assembly time. However, a process based assembly time estimation technique can provide some insight into assembly time. It is also likely that with a significant increase in the size of the training set the accuracy of the model will improve.

Several limitations of the analysis techniques presented in this paper may be causes for the high level of variation in the results. First, a relatively small amount of data was used for the analysis process. Only 200 process sheets were used for the artificial neural network training. The assembly of a vehicle requires three to five thousand process sheets. It is likely that a representative sample would consist of five hundred to one thousand process sheets including all areas of the vehicle. The data collection for this is currently underway for different areas of the vehicle and authored by different process planners.

Another cause of the variation may result from the inconsistency in the process instruction authorship itself. A significant level of variation was noticed in different vehicle areas as well as between different process sheet authors. This inconsistency could be reduced by enforcing a more strict authorship format. Authorship could be performed solely by selecting the appropriate word from a pre-determined set of words. This improved authoring process would reduce the variation in authorship and would also allow for automated data collection. An easier method of collecting information from the process sheets would allow for the analysis of more process sheets in a shorter amount of time. This would enable a more appropriate number of process sheets to be analyzed and used in the neural network training. This limitation is being addressed by an on-going industry sponsored research program that is looking at developing appropriate information models to support installation and process worksheet authoring.

Finally, additional information could be extracted from process sheets and used in the analysis. For example, part information is likely related to the part number in an existing database or software. For example information about a parts volume, mass, and material properties can be found in computer aided design software. This additional information could be extracted automatically and could further refine the accuracy of the assembly time prediction.

With the additional refinements to the analysis procedure presented here it is likely that a process based analysis will successfully compliment a product based assembly time estimation that will result in higher accuracies at an earlier time in the product life-cycle.

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