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Application of Artificial Intelligence to Measure the Productivity of an Assembly - Line Worker

Shivam Dhiman[1], Venkata Krishna Rao Pabolu[2], Divya Shrivastava[3]
[1, 2, 3] *Department of Mechanical Engineering, Shiv Nadar Institute of Eminence, Deemed to be University, Delhi-NCR, India*

Abstract:- Artificial Intelligence and its application became part of the manufacturing industry during the Industry 4.0 paradigm to resolve the manufacturing difficulties. Intelligent systems are robust in data monitoring and decision-making. Measurement of assembly worker productivity is important for organization economics. This research provides an intelligent technique to measure the productivity of an assembly-line worker using the computer vision. Furthermore, the productivity measures are used to model the work skill of the assembly worker for corresponding assembly task. Video learning technique is adapted to measure the worktime and productivity of the assembly worker from their work recordings. However, work skill is modeled in terms of the work time, assembly task's shop norm and the work time variance. A use-case example is given to demonstrate the research scope for a manual assembly line. The developed intelligent algorithm has measured the productivity of the assembly worker successfully. Furthermore, the results are compared with the manual measurement.

Keywords: Assembly line work monitoring, Intelligent productivity measuremen, Worker's work skill modelling. Video learning.

1. Introduction

The advancement of conventional production systems by the application of Artificial intelligence (AI) is the leading development during the fourth industrial revolution or Industry 4.0 [1]. Final assembly lines are part of product manufacturing, which assembles the parts of a product to make the final product. Workers are assigned to each assembly workstation in a manual assembly line to perform assembly operations or tasks [2]. However, the work assignment seeks a workload balance, based on the worker's working speed, work output rate, or required productivity. Moreover, a worker's work skill or craftsmanship plays a vital role in getting better work productivity and product quality. Measuring worker work productivity and modelling worker's assembly task skills are important for production economics and assembly line balancing, respectively [3]. The application of artificial intelligence techniques to measure the worker's work productivity and model the worker's assembly task skill is the primary objective of this research work for a manual assembly line system.

The application of artificial intelligence and machine learning techniques to solve manufacturing problems can be seen in the last decade. Anantrasirichai and Bull [4] discussed machine learning techniques and its four major dataset applications in creative industries. Those dataset types are script or text, sound or audio, image, and video type datasets. Xu *et al.* [5] used visual diagnostics to identify inefficiencies and locate anomalies in the assembly line. Knoch *et al*. [6] discussed a neural network-based real-time object detector technique to extract information of worker's hand movements, paths, and trajectories from a manual assembly video. This research intends to use object recognition techniques without neural networks to track worker movements and measure worker productivity.

Various measures are available in the literature to measure the productivity of an assembly line worker, such as productivity rate, standard time, cycle time, throughput rate per unit of work effort time, etc. Usubamatov *et al*. [7] used the measure productivity rate in car assembly line to calculate productivity losses. Hartanti *et al*. [8] used standard time as a measure to determine the productivity of a plastic product assembly line. Verma *et al*. [9] have used cycle time as a measure to assess the productivity of an automobile assembly line. Zhang *et al*. [10] used the throughput rate per unit of work effort time to measure the productivity of a collaborative assembly line. Worker task execution time (WTET) and assembly task repetition count are the measures used during this research to measure the productivity of an assembly line worker. Furthermore, the measured productivity values are used to model the worker assembly task skill.

Modelling of assembly worker task-performing skill is important for assembly line planning, worker selection, assembly line work assignment, and line balancing [11]. Pabolu *et al.* [12] used worker skill to calculate the comfortable work time of an assembly worker. Małachowski and Korytkowski [13] have developed an analytical tool to model worker skill to perform repetitive assembly tasks. Pabolu *et al*. [3] modelled the worker task skill in terms of the average task-performing time along with the time taken by the workers to perform the assembly operation. The proposed research uses a similar analogy in terms of standard productivity or shop norm given by Glover [14].

The application of artificial intelligence to measure assembly workers' work productivity and model their work skill is the research gap understood during the literature study. Video learning, object, and motion recognition techniques are adopted to measure the work productivity of an assembly line worker. The working speed or execution time of the assembly task is used to model the worker's assembly work skill.

The organization of this research work is as follows: A methodological framework to measure worker's work productivity using the intelligent algorithm is discussed in section 2. Methodology to model the worker's work skill in section 3. In section 4, a use-case illustration is given to explain the scope of the proposed work during the assembly line production planning. A brief discussion is done, about the work implications in section 5. Finally, conclusions are given with brief work prospects in Section 6.

2. Intelligent Systems for Worker's Work Measurement

The intelligent worker's work productivity measurement comprises two parts. Those are worker's work monitoring and worker's work productivity measurement. Video recording method is used to monitor the worker's work performance. Artificial intelligence techniques are adopted to create a worker's productivity measurement framework. An intelligent video learning algorithm is used to measure the worker's work productivity from the worker's work performance recordings. Corresponding details are explained in the following section.

A. Worker's Work Monitoring

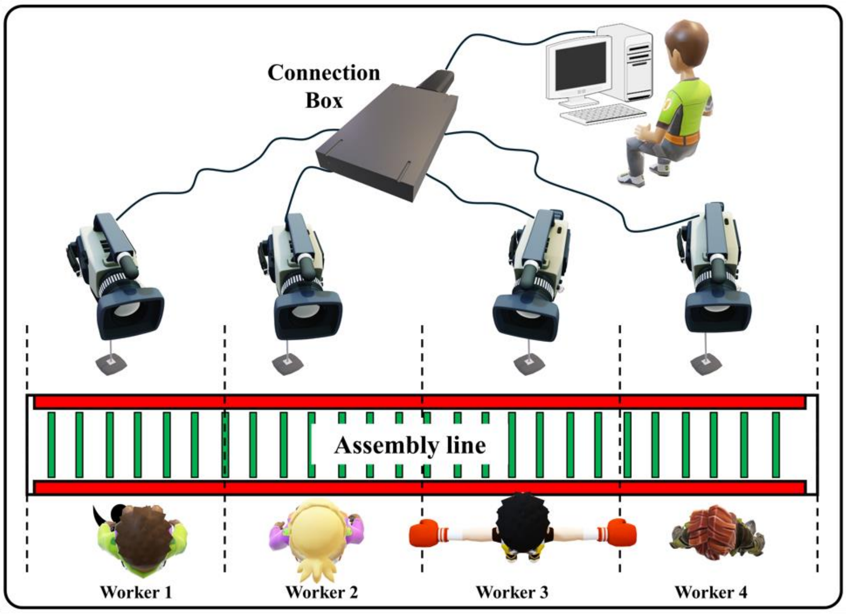

Fig 1. Worker's Work Monitoring

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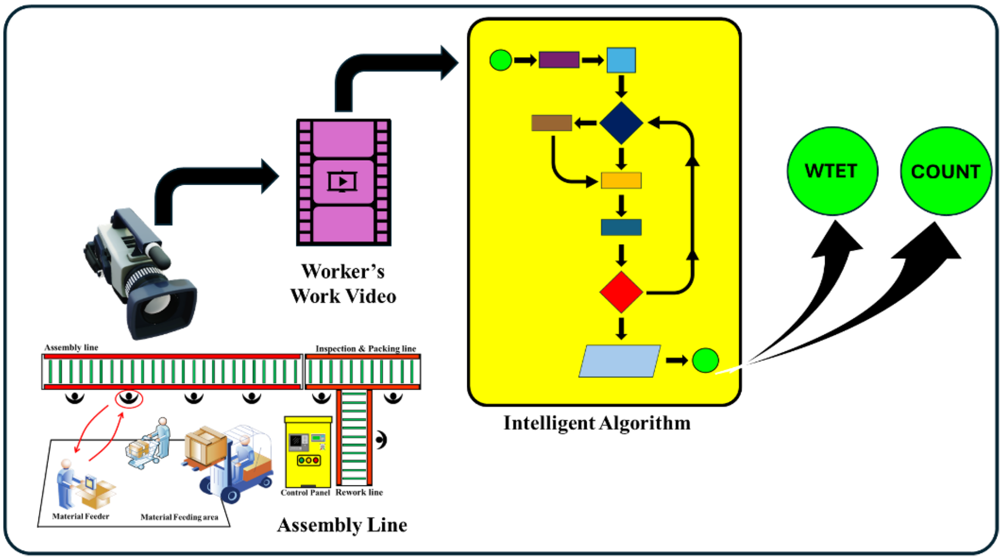

Fig 2. Measurement of worker's productivity

Video recording technique is used to monitor the work performance of each assembly line worker. Error! Not a valid bookmark self-reference. shows the arrangement of video recording cameras to monitor the worker's work performance. Individual cameras must be placed for each assembly worker to monitor their work performance. Moreover, it is essential to assign a single task to each assembly worker. Recorded videos can be saved into the database according to the worker and workstation number. The recorded videos are given to the intelligent video learning algorithm to measure the worker's work productivity.

B. Worker's Work Productivity Measurement

The worker's work productivity is measured in terms of worker task execution time (WTET) and COUNT of the assembly task repetitions, for work time. WTET is the amount of time in seconds spent by the assembly line worker to perform the assigned assembly task. However, COUNT is the measurement indicator which measures the assembly task repetitions for the worker's work time. **Error! Reference source not found.** shows the framework to measure the productivity of an assembly worker using an intelligent algorithm from the recorded worker's work monitoring video. A piece of code can be written in PYTHON as an intelligent algorithm to measure the worker's work productivity in terms of WTET and repetition COUNT. The intelligent algorithm detects the assembly worker as object. Furthermore, it detects the worker motion from the recorded video and fetches the timestamps of the assembly task's start time (TST) and end time (TET). Equation 1 is used to calculate the WTET.

$$WTET = (TET - TST) \qquad (1)$$

WTET : Worker's task execution time

TET : Worker's assembly task end time

TST : Worker's assembly task start time

A counter is introduced in the intelligent algorithm to count the number of task repetitions (*i.e.*, Repetitions COUNT) for the uploaded video duration. The measure 'COUNT' is used to assess the productivity of the worker. However, WTET is used to model the worker's assembly task skill for the given assembly task. Details of worker task skill modelling are discussed in the following section.

3. Worker Skill Modeling

The measured WTET is used to model the worker assembly task skill. Equation 2 is used to model the worker assembly task skill (S_{ht}). S_{ht} is a function of the task's *standard productivity* or *shop norm* (SN), Averaged worker task execution time (AWTET), and standard deviation (σ_t) of workers' WTETs. Where σ_t is calculated with task variance between the workers' WTET. Details of the standard productivity or shop norm are discussed by Glover [14]. Where the shop norm is the time taken by an average worker to complete the given assembly task.

S_{ht}	: Worker task skill for worker 'w' for task 't'
SN_t	: Task standard norm for task 't' in sec.
AWTET	: Averaged Worker task execution time in sec.
σ_t	: Task's Standard Deviation
RC	: Repetition Count

$$S_{ht} = \frac{(SN_t - AWTET)}{\sigma_t} \quad (2)$$

$$AWTET = \frac{\sum_{i=1}^{RC}(WTET_i)}{RC_{ht}} \quad (3)$$

$$\sigma_t = \frac{1}{RC}\sqrt{\sum_{i=1}^{RC}(AWTET - WTET_i)^2} \quad (4)$$

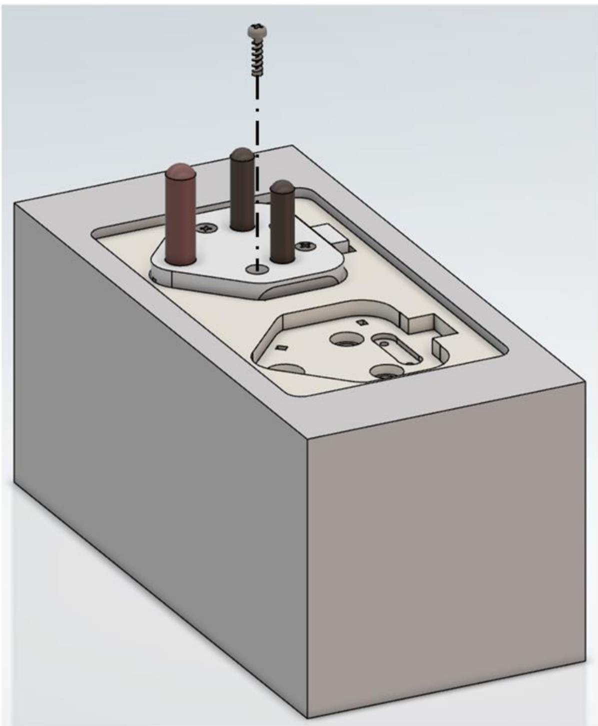

Fig 3. Assembly task

A positive worker's task skill represents that the worker is better than an average performer. Similarly, a negative S_{ht} represents that the worker had poor assembly task skill.

4. Use-Case Illustration

Let one of the assembly tasks of a product assembly is fixing the screw, as shown in **Error! Reference source not found.**. Where the worker must pick the defined screw from the bin, insert the screw into the screw slot and fix the screw with a screwdriver. Worker monitoring is done by taking a video recording, as shown in **Error! Reference source not found.**, while performing the screw-fixing operation.

Fig 4. **WTET comparison manual Vs computational**

The objective is to find,

1. The assembly time is taken by the worker to perform the screw fixing task for each repetition (*i.e.*, WTET)
2. Number of repetitions done by the assembly operator for a given time duration (*i.e.*, COUNT)
3. Model the screw-fixing task skill (*i.e.*, S_{ht}) of the worker. Where SN_t is 9 sec. and σ_t is 2.2.

An intelligent algorithm (*i.e.*, code) is written in Python to measure worker productivity in terms of WTET and COUNT. **Error! Reference source not found.** shows the results or output obtained from the intelligent algorithm after giving the work monitoring video as input. The output has three details. Those are WTET (**Error! Reference source not found.** showing as 'Time for operation'), repetition COUNT ('Total operation count'), and work recording duration ('Duration'). The obtained count and work recording duration is 5nos. and 50:01 seconds, respectively (from **Error! Reference source not found.**). **Table 1** shows obtained WTETs from the intelligent algorithm and stopwatch readings for the corresponding WTETs. Fig 5 shows the comparison of WTET between the stopwatch (*i.e*., manual) and an intelligent algorithm (*i.e*., computational).

Computationally measured WTET (from **Error! Reference source not found.**) is used to model the assembly task skill of the worker. Equation 2 is used to calculate the worker's assembly-task-skill for screw fixing operation. Averaged WTET (*i.e*., AWTET) is calculated in Table 1 from the measured WTETs; SN_t and σ_t are given as 9 sec. and 2.2, respectively. Substituting the AWTET, SN_t, and σ_t values into equation 2, worker task skill (*Sht*) is obtained as 0.0909. Indicates that the worker has higher skill than an average worker.

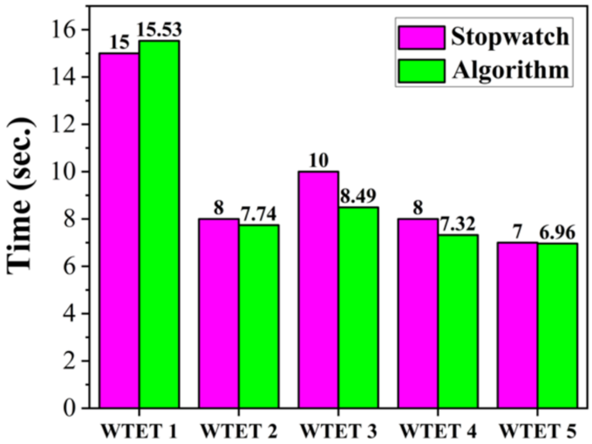

Fig 5. Video Recording of Worker's Work

Table 1. WTET Difference (Manual vs. computational)

Repetition	Stopwatch Reading (sec.)	Algorithm Results (sec.)	% Difference
WTET 1	15	15.5349	-4%
WTET 2	8	7.74237	3%
WTET 3	10	8.48846	15%
WTET 4	8	7.31795	9%
WTET 5	7	6.95813	1%
Total	**48**	**46.04181**	
AWTET	**9.6**	**9.2**	

5. Discussion

The developed intelligent algorithm measures the worker's productivity in terms of assembly task execution time (*i.e.*, WTET) and the number of repetitions (*i.e.*, repetition COUNT) from the given work recording video, which is helpful to make a move from human intelligence to machine intelligence for worker productivity monitoring. Furthermore, the measured productivity values are used to model the worker's assembly task skill (*i.e.*, S_{ht}). Moreover, the intelligent algorithm has measured worker productivity (*i.e.* task repetition count and work duration) accurately. Which eliminates manual errors in productivity monitoring. A time difference is noticed between the total work duration (*i.e.*, video duration) and the sum of the work time (*i.e.*, the sum of the WTETs) as 50:01 and 46:04 seconds, respectively, from **Error! Reference source not found.**. Which is the idle time between the task repetitions. The application of intelligent algorithms to measure the idle time of the worker is one of the prospects for this work.

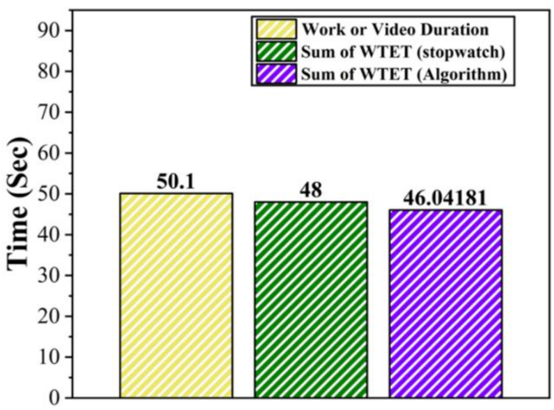

Fig 6. Total time differences

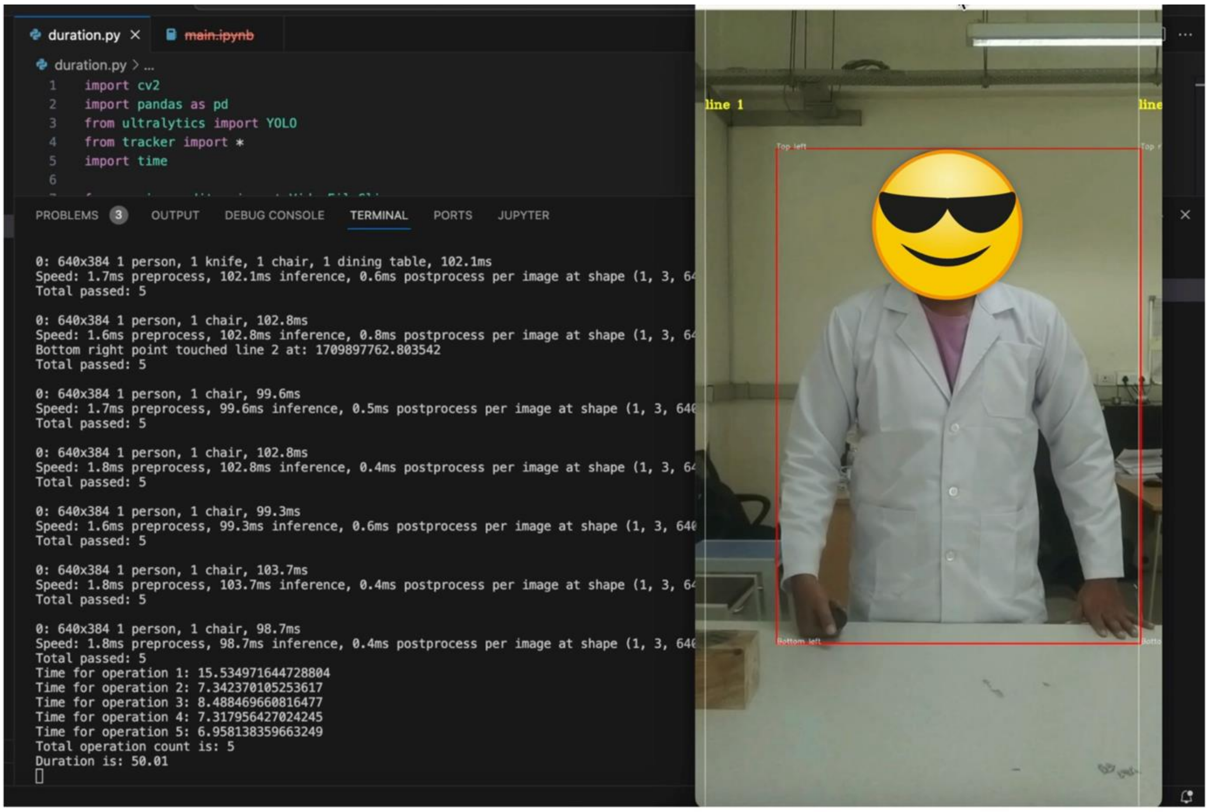

Fig 7. Output of Intelligent Algorithm

However, a slight difference is seen in the obtained results of each repetition (*i.e.* WTETs) using the proposed intelligent algorithm with the manual (from the Table 1). Since the intelligent algorithm divides the video into a set of frames. Improving the WTET calculation accuracy of the intelligent algorithm is one of the prospects for this research. Furthermore, the measurement of worker productivity when the worker performs more than one assembly task in an assembly workstation and the measurement of WTET of each assembly task using the intelligent algorithm are other prospects for this research work.

6. Conclusion

A methodology is given to monitor and measure an assembly line worker's work productivity using artificial intelligence. The methodology is comprised with three parts. Those are video monitoring, intelligent algorithms for productivity measurement and worker's assembly work skill modelling. Details of assembly workers' work recording, the intelligent algorithm for video learning to measure workers' work productivity, and assembly workers' task work skill modelling are elaborated. The video learning technique is adopted to make an intelligent algorithm, and the intelligent algorithm is used to measure the work productivity (*i.e.* WTETs and repetition COUNT, and work duration) of an assembly line worker. Worker assembly task skill modelling helps to compare the worker's work skill with other workers. A use case illustration is given to demonstrate the proposed methodology for screw fixing operation, which is a part of the product assembly. Where the intelligent algorithm showed better performance than manual productivity measurement. Furthermore, the intelligent algorithm found the worker's idle time between the repetitions of the assembly task. Application of the developed technique to measure assembly line workstation productivity while the assembly worker performs more than one assembly task, is the prospect of this research.

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References

[1] V. K. R. Pabolu, D. Shrivastava, and M. S. Kulkarni, "Intelligent Systems in Production Planning for an Assemble-to-Order Production System," in *Congress on Smart Computing Technologies*, J. C. Bansal, H. Sharma, and A. Chakravorty, Eds., in Smart Innovation, Systems and Technologies. Singapore: Springer Nature, 2023, pp. 177–190. doi: 10.1007/978-981-99-2468-4_14.

[2] V. K. R. Pabolu and D. Shrivastava, "A dynamic job rotation scheduling conceptual framework by a human representing digital twin," *Procedia CIRP*, vol. 104, pp. 1367–1372, Jan. 2021, doi: 10.1016/j.procir.2021.11.230.

[3] V. K. R. Pabolu, D. Shrivastava, and M. S. Kulkarni, "Modelling and prediction of worker task performance using a knowledge-based system application," *International Journal of Production Economics*, vol. 254, p. 108657, Dec. 2022, doi: 10.1016/j.ijpe.2022.108657.

[4] N. Anantrasirichai and D. Bull, "Artificial intelligence in the creative industries: a review," *Artif Intell Rev*, vol. 55, no. 1, pp. 589–656, Jan. 2022, doi: 10.1007/s10462-021-10039-7.

[5] P. Xu, H. Mei, L. Ren, and W. Chen, "ViDX: Visual Diagnostics of Assembly Line Performance in Smart Factories," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 1, pp. 291–300, Jan. 2017, doi: 10.1109/TVCG.2016.2598664.

[6] S. Knoch, S. Ponpathirkoottam, and T. Schwartz, "Video-to-Model: Unsupervised Trace Extraction from Videos for Process Discovery and Conformance Checking in Manual Assembly," in *Business Process Management*, D. Fahland, C. Ghidini, J. Becker, and M. Dumas, Eds., in Lecture Notes in Computer Science. Cham: Springer International Publishing, 2020, pp. 291–308. doi: 10.1007/978-3-030-58666-9_17.

[7] R. Usubamatov, A. R. Riza, and M. N. Murad, "A method for assessing productivity in unbuffered assembly processes," *Journal of Manufacturing Technology Management*, vol. 24, no. 1, pp. 123–139, Jan. 2013, doi: 10.1108/17410381311287526.

[8] L. P. S. Hartanti, "Work Measurement Approach to Determine Standard Time in Assembly Line," *Work Measurement Approach to Determine Standard Time in Assembly Line*, vol. 2, no. 10, Art. no. 10, 2016.

[9] N. Verma, P. Trivedi, and V. Agnihotri, "Productivity Improvement in Assembly Line of an Automobile Industry".

[10] Y.-J. Zhang, L. Liu, N. Huang, R. Radwin, and J. Li, "From Manual Operation to Collaborative Robot Assembly: An Integrated Model of Productivity and Ergonomic Performance," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 895–902, Apr. 2021, doi: 10.1109/LRA.2021.3052427.

[11] I. Gräßler, D. Roesmann, C. Cappello, and E. Steffen, "Skill-based worker assignment in a manual assembly line," *Procedia CIRP*, vol. 100, pp. 433–438, Jan. 2021, doi: 10.1016/j.procir.2021.05.100.

[12] V. K. R. Pabolu, D. Shrivastava, and M. S. Kulkarni, "A Dynamic System to Predict an Assembly Line Worker's Comfortable Work-Duration Time by Using the Machine Learning Technique," *Procedia CIRP*, vol. 106, pp. 270–275, Jan. 2022, doi: 10.1016/j.procir.2022.02.190.

[13] B. Małachowski and P. Korytkowski, "Competence-based performance model of multi-skilled workers," *Computers & Industrial Engineering*, vol. 91, pp. 165–177, Jan. 2016, doi: 10.1016/j.cie.2015.11.018.

[14] J. H. GLOVER, "Manufacturing Progress Functions I. an Alternative Model and Its Comparison with Existing Functions," *International Journal of Production Research*, vol. 4, no. 4, pp. 279–300, Jan. 1965, doi: 10.1080/00207546508919983.