

An error Prevention using Deep learning to Solve Disassembly Line Balancing Problem

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Abstract

The disassembly line has issues with balancing the disassembly, including worker errors and the influence of these errors on worker productivity, disassembly idle time, loss of smooth work, accumulation and blockage of some work stations, and the lack of effectiveness of other work stations. In this paper, a new novel technique for balancing the waste products disassembly line is proposed, and this method depends on the machine's vision to assist workers in performing the essential tasks. The findings of comparing the performance of workers with and without assistance with the proposed method were as follows: Worker productivity increased by 50%, idle time was reduced by 77.8%, the number of workstations was reduced by 33.3%, and the error rate was reduced by 81.5%.

Key words-disassembly line balancing; worker errors; worker productivity; disassembly idle time; machine vision.

I. INTRODUCTION

It has become progressively vital to increase the consumption rate of natural resources while lowering environmental degradation in the course of rapid social economic development. Re-cycling, as an efficient method of reusing and recycle damaged equipment, has become incredibly common in the production line. Within it, disassembly is now a focus in the associated field of research because it is the first critical step in the recycling process that affects both the ecosystem and the intangible value of businesses. Wasteful and unable to meet large-scale demand, disassembly at a single workstation [1] was developed as a more optimal way of accomplishing scale and automation for disassembly manufacturing [2]. But, due to the disassembly line's significant unbalancing problems, there has been a great deal of study done on how to balance the issue (DLBP). This research aims to fill in the gaps in the disassembly lines, which are represented in the problem of balancing the disassembly lines in general, and in this research, workers are assisted in carrying out tasks through deep learning, in order to avoid errors, which affects worker productivity, the reduction of work stations, and idle time.

The remainder of this paper is organized as follows: [Section II](#) outlines the kinds of disassembly lines and waste products need disassembly tasks, describes the machine vision and deep learning method based on images analysis. presents the type of fasteners and joints for assembly the products, and how to make dataset for those types of the fixtures to use in testing and training images. [Section III](#) defines the proposed model, and how to collect dataset for proposed model. [Section V](#) presents result and discussion for proposed model, and comparing with traditional disassembly products without assistant by proposed model. [Section VII](#) presents the conclusion and future work for proposed model to improve it, and contribute this model with industrial society.

II. LITERATURE REVIEW

Manufacturers face a significant challenge in determining the optimum solution for End of Life (EOL) products [3], [4]. Direct reuse, repair, recycle, disposal, and destruction are the five most common options for a product at the end of its life cycle. Direct reuse entails reusing the entire product for its intended purpose. Damaged parts are replaced in the repair option, resulting in a fully functional product. Reusing is the process of restoring used products to a level of quality that is comparable to that of new ones. Recycling is the process of recovering materials from discarded goods. The used products are disposed of in a landfill or incinerated. To develop a decision model to choose between these possibilities, numerous qualitative and quantitative aspects such as environmental impact, quality, regulatory factors, cost, and so on must be considered. Researcher utilized mathematical programming models extensively to build EOL option selection strategies. In reference [5] employ stochastic Dynamic Programming (DP) to establish a product recovery and disposal plan for a single product type based on the maximizing of net profit while taking into account important technical, ecological, and economic viability factors. In literature [6] was applied the methods provided a situations of recycling copiers and monitors, respectively, in follow-up articles. The EOL option of each item is determined by defining the objective function as the weighted sum of economic value and environmental effect, as defined in [7], [8] suggest a mixed integer program for determining the best component disposal approach based on net profit maximization. Based on the maximization of the overall return. The systematic separation of an assembly into its components, structural components, or other divisions is known as disassembly [9]. Because it allows for the selective separation of desirable pieces and materials, disassembly is a key process in material and product recovery [10]. Disassem-

bly lines for end-of-life products as shown in Fig. 1 is differ from assembly lines for new products in that assembly lines are single-product and assembly meals are known, whereas in disassembly lines as shown in Fig. 2, the products are known and disassembling duties are unknown, so researchers usually respond to just plan for different types of waste products. A single workstation, a disassembly cell, or a disassembly line can all perform disassembly procedures. Although a single workstation and disassembly cell is more versatile, a disassembly line provides the maximum productivity rate. In addition, the disassembly line is more suited to automated disassembly [11]. The disassembly line balance problem (DLBP) involves assigning disassembly tasks to a group of ordered disassembly stations while meeting disassembly precedence restrictions, minimizing the number of stations required, and minimizing the variation in idle periods between all stations [12], [13]. The first examples of disassembly line balancing algorithms were presented by Gungor and Gupta [14] and Gungor and Gupta [15], address the challenge of balancing disassembly lines in the presence of job failures (DLBP-F). The purpose of a disassembly line balance algorithm is to assign tasks to workstations in such a way that the effect of defective parts on the disassembly line is minimal. The effects of disassembly line associated problems are discussed by Gungor and Gupta [15]. They also show how several critical factors in disassembly can be used to balance a paced disassembly line by altering existing assembly line balancing principles. By dynamically structuring the disassembly system into several disassembly lines while considering line balance, varied process flows, and fulfilling different order due dates.

In the field of industrial automation, and automatic movement in three axes according to command program such as G-CODE in literature [16], the camera for machine vision and image processing technologies give unique solutions when moving to detect object automatically. Machine vision and image processing techniques have become more widely used in manufacturing processes as a result of industrial operations. Precision electronic component manufacture, high-quality textile production, integrated circuit fabrication, and a variety of other activities are among these activities. Where machine vision can be used efficiently, disassembly can be laborious, difficult, and dangerous in particular industries. Machine vision technology boosts production and gives firms that adopt it a leg up on the competition. This system is fast enough to meet the application environment's speed needs. The ability of industrial vision systems to match the speed requirements of an application without the need for special purpose hardware and achieve targeted throughput is one cost-saving benefit. Disassembly has traditionally been done without the assistance of human employees. Although human workers are capable of performing the job, they are unable to do it effectively due to the time-consuming nature of manual disassembly and a lack of understanding of the proper disassembly site. It is the goal of machine vision to analyze and understand visual data automatically. However, alternative visual inputs, such as video [17] or depth pictures [18], may be utilised [19]. Different computer vision tasks act at various levels of detail based on an input image. The simplest activities are the ones

that identify the overall image. Scene recognition [20] and image classification [21], [22] are two examples where a limited number of classes are used to classify the entire scene or the most prominent object in the image. Image captioning and action recognition [23], [24] are two different approaches to describing images. A finer level of detail is required for some jobs, such as labeling only a small portion of an image. There are a number of techniques that can be used for object detection, such as object recognition [25]. Part detection [26] and pose estimation [27] recognize and locate the semantic pieces that constitute the objects, and pose estimation predicts the inner spatial arrangement of the objects. An object's state (appearance, lack, fault) can be determined with great accuracy by using the single-shot object identification model YOLOv4 (YOLO is software algorithm means you only live once)[28]. The model was chosen because it provides real-time results with excellent accuracy on the locations of attachment and implementation. A version of Tensor RT run time was used to speed up the trained model's inference time. Micro-calibration, layer merging, and multi-stream implementation are just some of the optimization methods used by the Tensor. To train the model, we used 100 training images with 500 object instances and 50 validation images with 150 object instances by using An algorithm to test and train joint part image of waste products to detect joints for assembly product as shown in algorithm 1, and in algorithm 2 for detect joint place in the edge and inside of product, also a flowchart of detecting, testing, and training as shown in Fig. 3. An average of 150 states are used for each of the 60 object classes in the training data. It is possible to use a limited training set due to the significant volatility across disassembly sections and the low intra-class variance. A variety of EOL products were used in the training session. After 1000 training sessions, the average accuracy at the 50% of training by mean Average Precision (mAP) was 95.81%. To use these rating scales, it's clear that the model can accurately predict all of the categories. Parts and small components that change their appearance only slightly after disassembly can make it difficult to detect items and faults. Detecting a part's correct vertical attachment in the mount would be difficult with the camera perspective as shown in Fig. 4 currently set. It is impossible to determine the correct torque value by sight, so only the bolts are inspected. The pieces can emerge in a variety of shapes, such as spot spot welding, which necessitates additional training data to be recognized accurately. A single individual spent around five hours collecting training, validation, and comment data on all instances of the object. With 34 tasks steps and 50 parts classes to remark on, this time investment looks appropriate given the product's high complexity, as it may be performed by inexperienced employees. The database is used for inference.

III. PROPOSED MODEL

Fig. 5 illustrates a main highlight of the proposed model, as the model is an assistant for workers to avoid errors due to omission or lack of knowledge, and the model as shown in Fig. 2 is used in the disassembly lines to solve the problem of unbalanced dismantling lines, where the model can be divided into four main sections:



Fig. 1. Traditional parallel layout disassembly line dividing to three lines, every line assigned to one type of waste product.

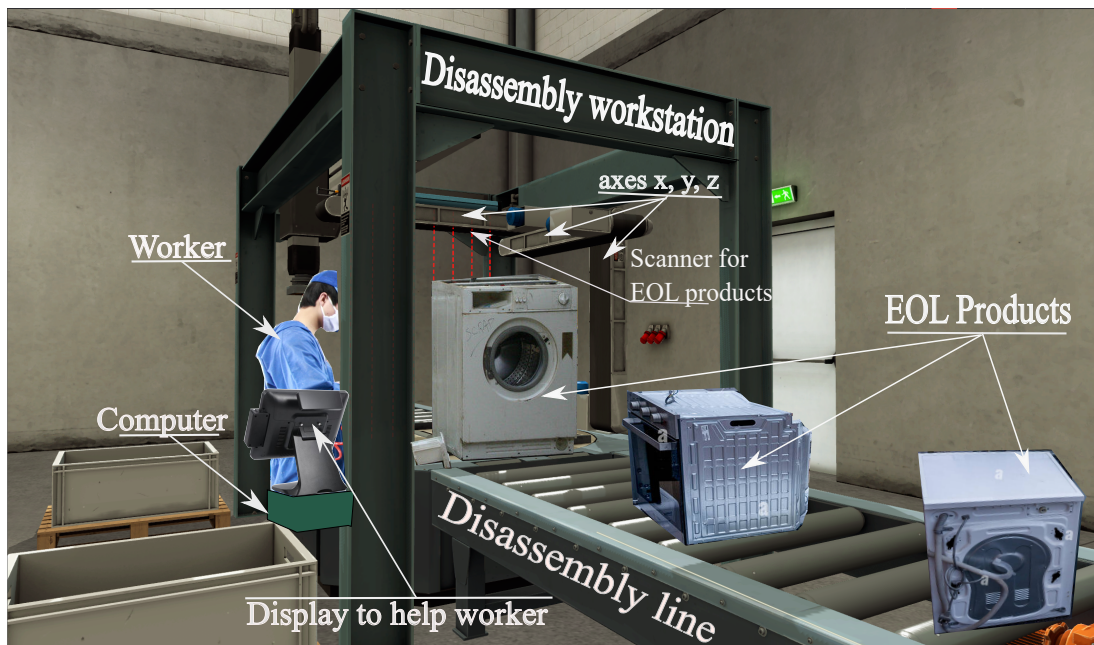


Fig. 2. The disassembly workstation attachment with proposed model to assist worker

- 1) Taking an image of the EOL product.
- 2) Improving the image through computer vision and deep learning.
- 3) Call the database, test and train the available image of the place of fastener and joints of the EOL product.
- 4) Using related database images, train an image to identify and choose the best tool for removing a component from a waste device.

Fig. 6 show the flowchart of proposed model and algorithms to assist disassembly worker in workstation aim to make a decision just in time, Artificial Neural Network (ANN) was used in this paper to training data with dataset, and send decision according to optimizing objective function such as

remove hazard parts early, and remove demand parts after that.

A. Databases

The database in this paper was collected by the authors, and it was divided according to the different types of fastening of products such as stud fastening, welding jointing, adhesive bonding, rivet bonding and so on.

B. Collecting a database of types of joints of products

The images of the fasteners and attachments were collected by a high-resolution camera, and those images were classified by the labeling program from the python package as shown

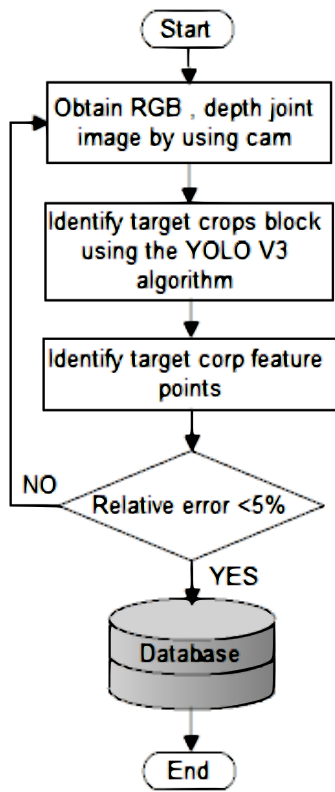


Fig. 3. The flowchart of testing and training images in YOLO algorithm in TensorFlow navigator program.

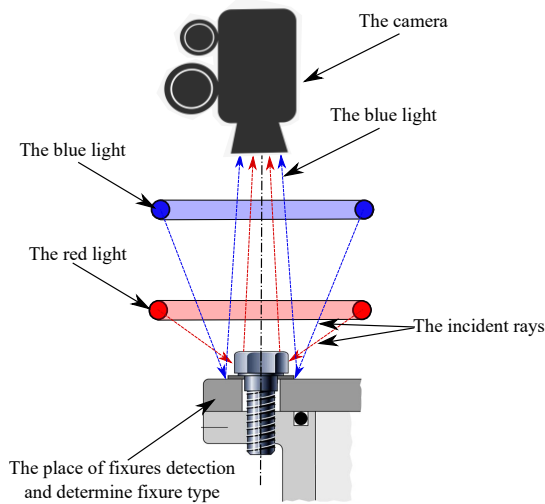


Fig. 4. Detection of the location of waste product connections and fasteners, red and blue lights to focus and remove the light reflected from the reflective metal surface

in Fig. 7, where the authors created new database for various types of joints and fasteners using Labeling software, for example of those database as shown in Fig. 8 .

C. Labeling software

Labellmg was used to categorize the data, which is a good and simple data classification application that is simple to enter and classify and beneficial in computer vision. Label of joints are used to aid in the identification of data components that the model will be trained to recognize in unlabeled data sets. For computer vision and high-performance model construction, high-quality data sets are required. The philosophy of garbage is followed when creating computer vision models, which means that identifying images carefully and precisely is crucial. Tagging in VOC XML or YOLO text files is supported by LabelImg.

IV. DIVIDING DATABASE OF WASTE PRODUCTS

According to detecte the name of the component, manufacturer, part number and component level, the inherent processing method of the component is found in the recycling treatment method of the material / each component, and the processing method of the component is found (in some cases, based on the way of the component is assembled. If there is no inherent treatment of the part, it is determined whether the material that makes up the part is single or composite in this case the proposed model estimating and recognizing the name of the component, manufacturer, part number and component level before send to monitor. The material that constitutes the part is a material, the processing method of searching for the material in the foundation the material / the circulation method of each part. For a material, if there is only one method of treatment, it is determined by one method; if there are multiple processing methods, it is processed in units [(purchase price per processor of the material)] pre-processing (crushing). Estimate costs, compare them, and then make decisions in a higher way The cost of pre-processing (crushing). The purchase price of each processor of the material is recorded according to the recycling method of the material / part and is dominated by the material. The cost of intestinal internal pre-processing (crushing) is recorded in the standard treatment method of the model. For example, in a product, the separation / resolution task order of harmful / dangerous and reusable components in a product is from the 9th in the product disassembly method from degree 2 to degree 6. The disassembly order is 9 to harmful / dangerous parts, or non-reusable parts, all of which are parts with disassembly order 1, 2, 3, 4, 5, and 6. In the disassembly method, the parts that are determined to be unsuitable are guided to form the part number of the part in turn in the disassembly order. Moreover, based on the leading part number, the product specification information led by the product specification database is led by the component. According to the component information of the guiding part, the processing mode of the part is reanalyzed by material / part. Search the database for how to handle the cycle. The material / Recycling method for each part database records the processing method of each part and the processing

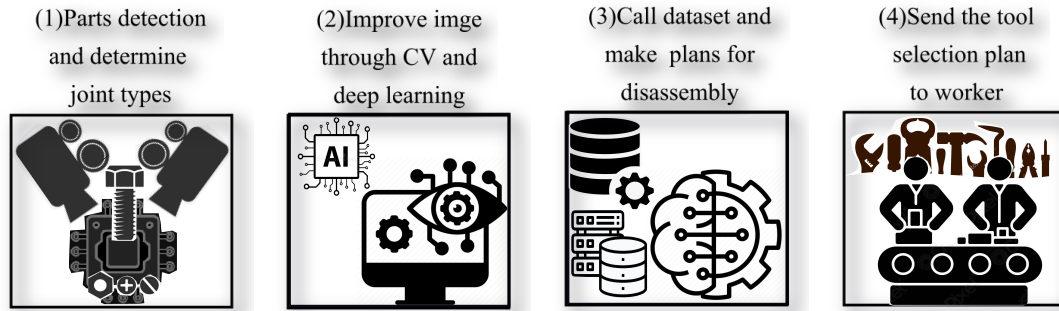


Fig. 5. Schematic diagram showing design innovation and the techniques to solve disassembly line balancing problem

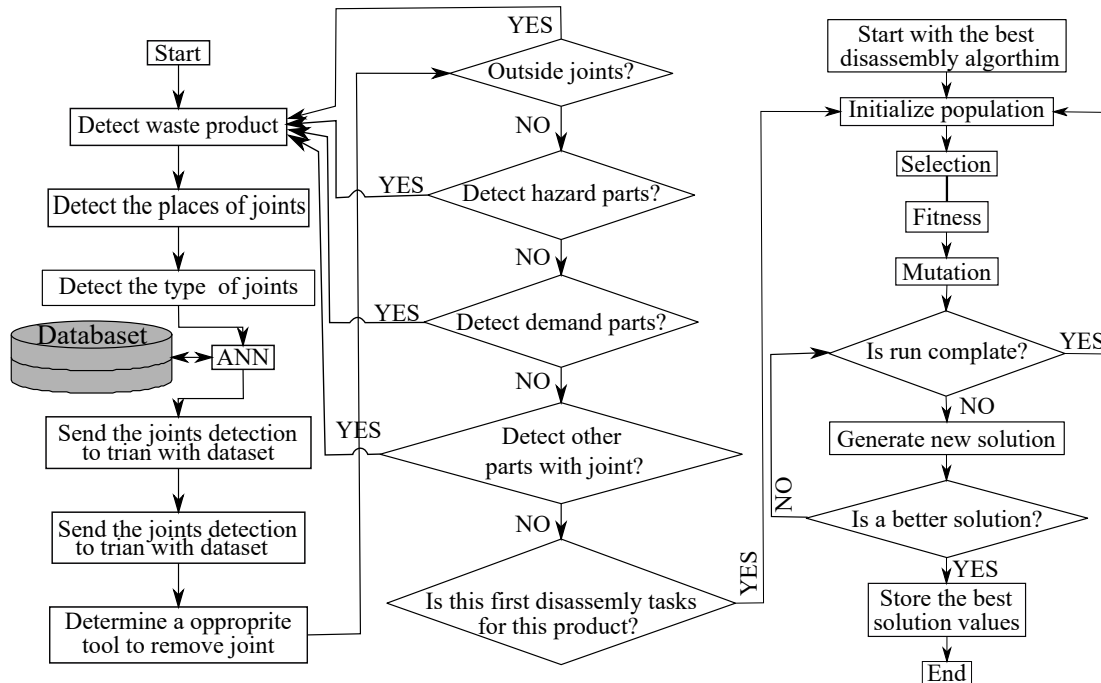


Fig. 6. Flowchart of proposed model and algorithms to assist disassembly worker in workstation aim to make a decision just in time.

method information of the material. When searching for part processing method information, execute in the following order.

(1) Product specification database

In this model, if necessary, a product specification information database is written, which records the product specification information and the product specification information as the processing object as shown in Fig. 9. Product specification information is written by product designers at or after design. The registration of a database regulating information is performed by a product manufacturing company or a manufacturer commissioned by the manufacturing company, etc, consideration may be given to filling in the information. Product specification information includes: manufacturing company name, product type, product name, shape name, manufacturing year, manufacturing number, component information (product description, part number, component manufacturer, part specification, material, shape size, quality, harmful substance or reusable component). Use force, decomposition method (disassembly order, necessary tools, disassembly indicator, etc.), standard disassembly project number (time), etc. The

above disassembly method, including the designer of the waste product, and so on, must be determined in advance, but at least one disassembly method shall be determined, in which the original code representing the part to be removed shall be used to represent the component as shown in Fig. 10. Therefore, according to the disassembly method, each part of the separation degree is accompanied by an inherent code indicating the above part. Of course, according to the method of disassembly.

(2) Regulations / specifications pedestal

A database that stores information on regulations or specifications relating to the sale of products or waste disposal, Such information-for example, harmful goods or dangerous products that cannot be buried in harmful, dangerous or safe final disposal sites, as well as dangerous goods or dangerous parts that should not be buried at the final disposal site, In the managed final disposal area, harmful substances and dangerous substances that should not be filled, It's information. Legal information will be obtained through bulletins, etc., and its database will be made available. In addition, with regard to

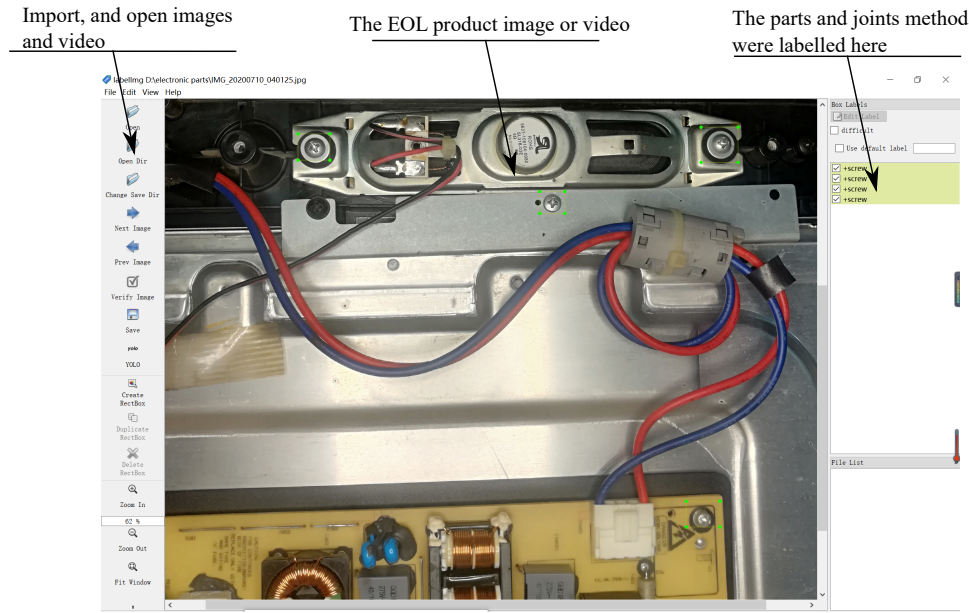


Fig. 7. LabellMag software interface used to make databases for joints and fasteners of assembly EOL products.



Fig. 8. The example sample from the dataset of nuts in common shape using to joint and fix products in the assembly line at the beginning of manufacturing.

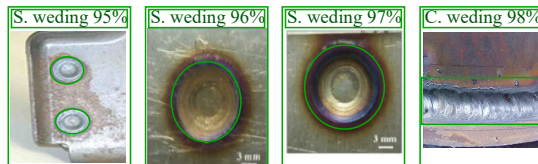


Fig. 9. The instant sample of testing and training connection place of common products, the acceptance of training must be greater than 95% degree of certainty in a joint-type image to make strong decision when send message to worker.

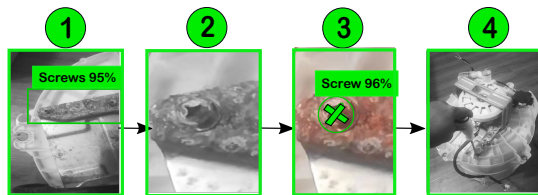


Fig. 10. The instant sample of acceptance of training with 95% a degree of certainty and confidence of joint-type.

specification information, we collect more information about the specification and database it than during the implementation of the specification. At this time, for example, it is good to sort out the data by product classification.

(3) Database of materials / by part recycle

Specific recycling and disposal methods of materials / components, in particular harmful substances, components

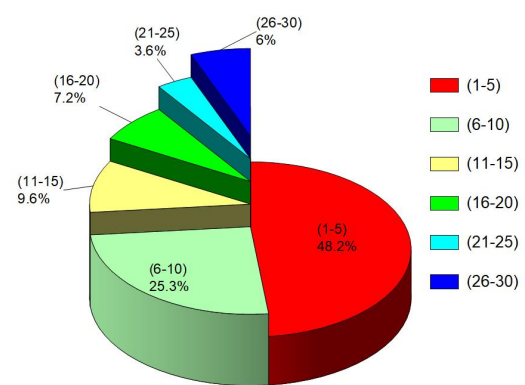


Fig. 11. The errors of workers distributing according to grouping of accumulative errors.

containing harmful substances or hazardous substances, treatment of components containing hazardous substances (non-disassembly treatment, regeneration treatment, disposal methods, etc.), or information provided by suppliers who can process such materials. Contacts, processing costs, and so on) are stored on the database. It is better to test according to materials, parts, etc. Information required for second-hand components, purchase information for various recycled materials, purchase price information for wastes of various recycled materials, information on the acceptability of various demand processors, various harmful / dangerous processors or all kinds

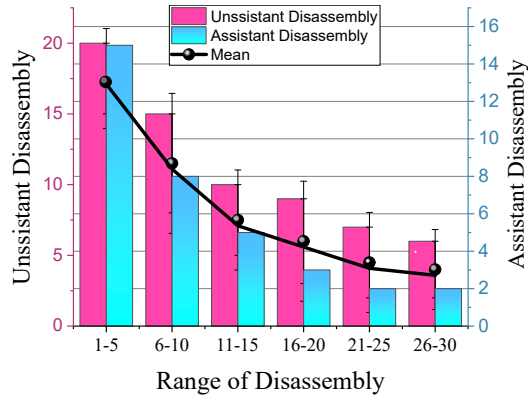


Fig. 12. The comparison of grouping of errors, and reduction of errors as result of repeating disassembly tasks.

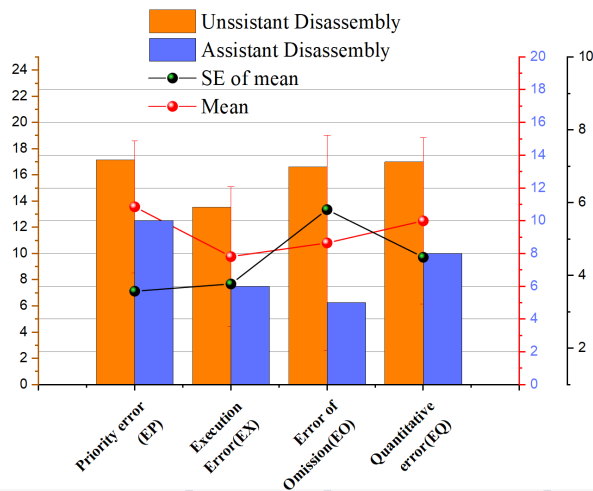


Fig. 13. The comparison of UD and AD according of type of errors

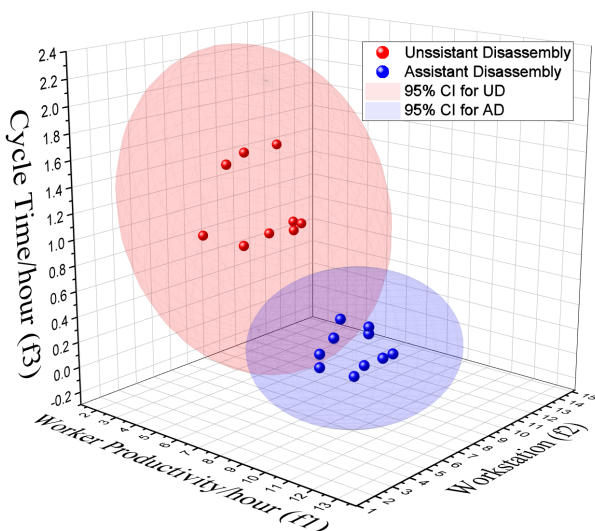


Fig. 14. The optimal ten solutions of UD and AD filtering by Pareto set for f_1, f_2, f_3

of final disposal, Store the information of the second-hand part buyer or all kinds of processors (owner's name, address, telephone number, fax number, etc.) and store it in the database of the freight rate of all kinds of carriers.

(4) Specification of database

It is the database specification information of the various specification information of the model that stores the waste disposal, and there is the processing cost information, the cost of processing per hour per unit, the unit weight or the crushing cost of the unit. Every database factory needs to own it, every database is managed conservatively, and every exclusive factory needs to own it, every database needs to own it, and every unique factory needs to own it.

(5) Loop processing method decision processor

The cycle treatment method decision treatment unit is equipped with a cycle treatment method decision unit for storing the model treatment method, a treatment decision number order correction character, and a treatment decision number order creation unit (3 years old) (the cycle treatment includes the disposal of waste treatment). With the passage of the times, new recycling and waste disposal methods are constantly changing. It is necessary to modify the rule or the cyclic processing dispatch according to the rule at any time.

(6) The circular treatment method

Decision processing method connects the above four databases, based on the information of each database, determines the treatment method of the waste product, and writes it out in the order of the cyclic treatment method.

A. Types of most fasteners in the products

Fasteners are a broad category of tools that include screws, nuts, and bolts that have the same purpose: to mechanically hold objects together. Glue, for example, can serve this purpose, but glue is not a form of fastener. As a result, the definition is to be expended. Objects are mechanically held together by hardware fasteners.

Fasteners usually produce a non-permanent connection. In other words, if fasteners to connect two parts are used, should be able to remove it without causing any damage to the separate portions. A welded junction also used to collect two or more parts but with permanent link that can only be removed by cutting. on the other hand, would not be the same. Rivets, which are classified as fasteners yet generate permanent joins.

Though most fasteners produce a non-permanent joint, this does not imply that only use them when it needs to disassemble products, nor does it imply that the joint is in any way weak. Fasteners can reliably hold objects together that are subjected to a lot of stress. That means they're suitable for both permanent and non-permanent joints, giving products flexibility in terms of the products.

B. Notation

This list contains mathematical model notations used in this paper.

f_1	Increase worker productivity
f_2	Minimize the the number of workstations
f_3	Minimize the idle time
f_4	Minimize worker errors
t_c	Cycle time of workstations to remove parts in one or more tasks
t_k	The idle time
$t_{o.t}$	Lost time outside the disassembly idle time due to technical reasons
t_n	An optional period of time to study the functionality of the disassembling equipment
θ_n	The average time required to reset and calibrate the disassembling equipment
θ_p	The total time required for disassembling equipment to perform its functions
u	Random variable an independent
ϵ	A decreasing ratio of cost
t_{po}	time of all technical effects to disassembly line components

C. The mathematical model of the proposed Multi-objective model

1) *The model of productivity*: The main objective Q_{max} aim to maximize the productivity of the worker, to obtain this objective Q_{max} based on errors reduction relating to this following equation:

$$\text{maximize } f_1 = \sum_{E=1}^E Q \quad (1)$$

Also technical productivity can be calculated by this equation:

$$Q = \frac{w_p}{\frac{T_d}{w_q} + T_a + \frac{w_p w_q \sum T_i}{n} \left[1 + \frac{2\delta(1-\delta^{n-1})}{1-\delta} \right]} \quad (2)$$

Where w_p refer to workstation in disassembly line, and $w_p = 1$; T_d components disassembly in cycle time; T_a adjusting time (component/min); T_i idle time loss at single workstation (min/component); w_q is the quantity of sequential workstations.

The relationship between productivity Q_c and quantity of workstations W is shown in the equation (3) with a special cases, where productivity increases at the beginning with the increase in the quantity of workstations and after that it decreases sharply, there is an ideal value for the quantity of workstations W , which achieve the greatest productivity Q_{max} , this ideal value can be obtained by taking the first derivative and equating it with zero in equation (4)

$$Q_c = f(W) \quad (3)$$

$$\frac{dQ_w}{dw} = 0 \quad (4)$$

2) *Model of workstations*: The second objective assignment is determine to reduce the workstations, in actual terms as work for the limitation number of workstations

$$\text{Minimize } f_2 = \sum_{E=1}^n W_{optimum} \quad (5)$$

$$W_{min} \leq W_{optimum} \leq W_{max} \quad (6)$$

$$W_{optimum} = \sqrt{\frac{t_{po}}{t_c}} = \sqrt{\frac{t_{po}}{\omega_c \tau_B}} \quad (7)$$

$$W_{max} = \mu \sqrt{\frac{\alpha}{\beta}} \quad (8)$$

$$\lambda = \sqrt{\frac{K_{tec} + N_y m}{K_{tec} + N_y (m + \frac{1}{\epsilon})}} \quad (9)$$

The quantity of sections at disassembly line can be obtain by the relationship:

$$n_s = \frac{W_{Tex}}{W_{max}} \quad (10)$$

Where W_{Tex} is quantity of workstations in disassembly line related to technical plan

$$\lambda = \frac{Q_2}{Q_1} = \epsilon \varphi \frac{K_{tec} + N_y (m_c + 1)}{k_{tec} \sigma + N_y (m_c \delta_\varphi + \frac{1}{\epsilon})} \quad (11)$$

Where Q_1 work productivity achieved by equipment and technology of the first type (UD), and Q_2 work productivity achieved by equipment and technology of the second type (AD), φ growth of workstations productivity, k_{tec} is a parameter describing the degree of technical processing of the disassembly line, N_y investment period by years, σ is the variation of disassembly tools cost, ϵ is decreasing ratio of cost, δ_φ is the variation of disassembly for waste products, m_c is cost factor.

3) *Model of Idling time*: Total losses time is one of the most important factor attesting in productivity and work ability of the workstation. In this objective is assign to minimum of total idling time of all workstations, taking into consideration balance of workstations:

$$\text{min } f_3 = \sum_{E=1}^n (W_E \cdot t_c - t_E)^2 \quad (12)$$

The total idle time can be calculated:

$$\sum t_E = \sum t_c + \sum t_{o.t} + \sum t_n \quad (13)$$

One of the most significant elements impacting productivity and the capacity of the workstation to function is total losses time, which is measured using equation (14)

$$\sum t_E = \frac{\sum \theta_n}{z} = \frac{\theta_n}{\theta_p} \quad (14)$$

4) *Model of Errors*:

$$\text{min } f_4 = \sum_{E=1}^n E \quad (15)$$

This equation may be used to gather all of the errors that happened during the disassembly tasks to removal parts in disassembly line:

$$\sum_{E=1}^n E_T = E_{EP} + E_{EX} + E_{EO} + E_{EQ} \quad (16)$$

where EP refers to priority error; EX : execution error; EO : error of omission; EQ : quantitative error.

D. Constraints:

Equations(17-20) ensures that all parts are disassembled and each disassembly work is located in different positions in the disassembly sequence.

$$\sum_{i=1}^n \sum_{k=1}^n w_{ik} = \frac{(n-1).n}{2} \quad (17)$$

$$w_{ik} = 0, \forall i \quad (18)$$

$$w_{ik} + w_{ki} = 1, \forall i, \forall k, i \neq k \quad (19)$$

$$\sum_{j=1}^n w_{ik} \neq \sum_{k=1}^n w_{i'k}, \forall i, i' \neq i' \quad (20)$$

Equation (21) for the precedence constraint of the disassembly sequence, the position of a work in the disassembly sequence is less than the position of the work before the disassembly sequence have been completed.

$$\sum_{k=1}^n w_{ik} > \sum_{k=1}^n w_{uk}, \forall i, \forall u \in \{u | a_{ui} = 1\} \quad (21)$$

$$p_i = \sum_{k=1}^n w_{ik} + 1, \forall i \quad (22)$$

$$T_j = \sum_{k=1}^n \left((t_k + \sum_{k=1}^n (s_{ik} \times w_{ik} + t_s \times z_k) \times v_{jk} \right), \forall j \quad (23)$$

$$T_j \leq T_c, \forall j \quad (24)$$

$$\sum_{j=1}^j v_{ij} = 1, \forall i \quad (25)$$

$$v_{ij} \leq \sum_{e=1}^j v_{1e}, \forall j, \forall i, \forall l \in \{v | p_l < p_i\} \quad (26)$$

$$z_j = 1, \forall j \in \{j | p_j \neq 1, r_j \neq r_v, v \in \{v | p_v = p_j - 1\}\} \quad (27)$$

$$v_{ik}, w_{ij}, z_j, S_k \in \{0, 1\} \forall i, \forall j, \forall k \quad (28)$$

Equation (22) determines the position of every work in the disassembly Progress. Equation (23) determine the working time of every workstation, including the work time of disassembling work. Equation (24) is a losses time constraint, indicating that working time doesn't surpass the idle time. Equation (25) is a work allocation constraint to ensure that all works are allocated, furthermore, every disassembly work must be relegated to a workstation. Equation (26) is the priority relationship constraint of work allocation, which indicates that the pre task in the disassembly sequence is assigned to the workstation first. Equation (27) determine whether the disassembly work is adjusted or not, only if the work is adjusted. The latter work needs to perform the adjustment operation before the disassembly operation begins and change the placement position of the obselete. Equation (28) defines the 0-1 variables of v_{ik} , w_{ij} , Z_j , and W_k .

TABLE I
THE DESCRIPTION OF TASKS TO DISASSEMBLE WASHING MACHINE.

No.	Description	Time/h	D	P
1	Back cover	0.0029	-x	0
2	Water level control's screws	0.0029	+z	1
3	Remove the water level control	0.0027	+z	2
4	Remove the plug cable's screw	0.0055	-z	3
5	Removing electrical cable plugs	0.0033	-z	4
6	Remove the plug cable	0.0103	+x	1
7	Remove any cables with no plugs	0.0059	+x	5,11
8	Cut the cables plugs	0.0039	-x	6
9	Cut cable fixing rings	0.0089	-y	8
10	Remove control board and door	0.0039	-x	7
11	Remove capacitor	0.0049	-y	10
12	Remove the bottom cover	0.0033	+y	9
13	Remove the drain hose	0.0055	+z	12
14	Remove inverter	0.0043	-x	13,14,15
15	Remove tub ring	0.0059	-y	16
16	Pick up tub	0.0071	+z	17
17	Remove suspension rod	0.0031	+z	19
18	Remove outer case	0.0053	-x	20
19	Remove motor case's screws	0.0027	+y	18
20	Remove motor case	0.0103	+y	11
21	Remove pivot motor's nut	0.0029	+y	21,22
22	Remove motor stater	0.0039	+y	20
23	Remove motor bracket	0.0027	+y	21
24	Remove plaster's screw	0.0071	+y	22
25	Remove drum's screw	0.0027	+y	23
26	Remove brake motor	0.0053	+y	24
27	Remove water inlet-valve's screw	0.0027	+y	25
28	Remove water inlet-valve	0.0087	+z	27
29	Remove water inlet hose	0.0095	+z	28
30	Remove stop gear	0.0087	-z	29
31	Remove spring	0.0031	-z	30
32	Remove drum	0.0055	-y	31
33	Remove tub	0.0029	-y	32
34	Disassembly drum	0.0039	+y	33

Algorithm 1 An algorithm to test and train joint part image of waste products to detect joints for assembly product

Require: Label of joint head area

Ensure: Classification of joint types

```

for  $i \leftarrow 1$  do                                ▷ to shift total parts
  for  $j \leftarrow 1$  do                                ▷ to stage total parts
    for  $k \leftarrow 1$  do                                ▷ to filter total parts
       $f_e$  = integral of sub frame
      Update weight_parts
      Update weight_ collection and joint type
      if  $f_e < \text{weight\_parts}$  then
        break for k_loop
      else if  $f_{total} = \sum f_e$  then
        end if
      end for
    end for
  if  $f_{total} < \text{weight\_parts}$  then
    Output not joint
  else if Output = interest then
    end if
  end for

```


Algorithm 2 Algorithm to ensure testing and training images and acceptance at a level higher than 95 percent

Require: Label of joint head area

Ensure: Classification of joint types

```

for  $x \leftarrow 1$  do
  for  $y \leftarrow 1$  do
    if  $\text{Img}(x,y) > \text{threshold}$  then  $\text{match\_found} == 0$ 
    else if Adjacent part pixel  $< \text{threshold}$  then
      for  $n$  in 1 to (No parts found) do
        if  $(x,y)$  fall within a small distance of joint
part  $n$  then
           $\text{match\_found} == 1$ 
        end if
      end for
    if  $\text{match\_found} == 1$  then
      Increase the waste product joint  $n$  to include
(x,y)
    else if Add new  $(x,y)$  then
      end if
    end if
  end for
end for

```

V. RESULTS AND DISCUSSION

Various criteria were created to examine the frequency of waste product disassembly errors. A total of 10 participants were included in this evaluation; each subject was able to complete at least this many assignments during the experiment.

Table. I the description of washing machine disassembly, the time per hour to determine the labor productivity, where (D) mean the direction of removal part, and (P) represent the precedence of parts.

A. Preventative measures for errors

The process of disassembling a complex washing machine with the suggested disassembly assistance system (experimental group) and a control group without the assistance system is referred to as experimental setup. For the disassembly tasks, two major parts similar workstations were set up, as shown in Fig. 2. The disassembly process consists of 34 separate work processes, including 155 tasks for removing screws, 30 steps for removing cable connections, 30 cutting operations, and 2 remove hazardous part (capacitors), among other things. Materials used in disassembly parts include polymer, metal, steel, fiberglass, and electrical components. The sizes range from $1mm^2$ cable wire to a $(70 \times 40 \times 40)cm^3$ volume of outside case. The wide range of disassembly procedures, materials, and part sizes ensures that the disassembly problem is correctly identified. Configure data for various product types. Furthermore, the disassembly method' adaptability allows the results to be applied to other products and new assistance systems. Ten test subjects disassembled the washing machine for 10 hours in both the experimental and control groups. Each test person can disassemble at least 50 washing machines at this time. Different degrees of manual disassembly expertise may be present among those who have never disassembled a

washing machine. Except for their working instructions, they were not given any other information on the disassembly procedure. The authors were in charge of the entire procedure and monitored it. Noted carefully log every disassembly errors that happens throughout the disassembly process. Worker errors from all six disassembling groups were combined to trace the test subject's training process over the course of disassembly. Errors are counted in aggregate without being classified into error kinds in this analysis. The amount of errors reduces as the number of conducted disassembly increases for both the assistant disassembly (AD) and unassisted disassembly (UD) sets (Table. II). The (AD) group reported a 92.11% reduction in mean errors from 15.2 errors in disassembling errors (1-5) to an average of 1.2 errors in disassembling (26-30). The UD group has 7.5 errors in disassembling (1-5) and 1.0 error in disassembling (26-30), which is an 86.7% reduction.

while both sets demonstrate error reduction progress, an errors comparison of random selection from the six groups, the assistant disassembly set creates fewer errors states at each step of the disassembly process, according of variance from 12.5 to 8 at last group, upper and lower of 95% confidence interval (CI) from 49.2 to -14.26 in table. III.

Fig. 11 shows the maximum number of errors in both groups appeared in group (1-5) gain about 45%, that because the worker has not know the exactly processes of disassembly at first time.

Fig. 12 shows a rapidly and dramatically reduces during the first 15 disassembly steps. The number of disassembly faults remains largely consistent at a lower level for the next fifteen disassembling steps. As a result, it's reasonable to assume that there will be a period of early training followed by a period of skilled worker. When implementing the suggested assist system, the total number of errors in 30 individual disassembling lowers from an average of 15.2 errors in the UD set to 7.2 errors, corresponding to a 52.67% errors reduction. Both the initial training phase and the subsequent skill phase are affected by the findings.

In Table. V the AD group has a narrower quarterlies of total errors, indicating that the number of errors in this group is statistically less dispersed, disassembling errors lowers from an average of 13.5 errors in the UD set to 8.83 errors in AD, corresponding to a 34.6% errors reduction. A more stable disassembly environment is indicated by a smaller spread across the number of test individuals.

In Table. VI the AD model's overall error reduction effect has a variety of worker productivity was increased from 5 washing machine/hour, to 10 machine/hour. Second, due to reduce errors, the idle time (IT) was reduced from 0.9 h in UD model, to 0.2 h in AD model, Third, the number of workstations was reduced as a result of reduce the errors in disassembly, the workstation from 6 workstations in case of UD model, to 4 workstations in case of AD model. Linear relationship was assumed between each objective and the amount of total errors because quantifying these beneficial effects is challenging.

B. The effect of error on worker productivity

In Fig. 13 it has been observed that errors adversely affect the productivity of workers, and the reason is that the large number of errors increases the time of dismantling, which reduces the number of products per hour, and when comparing between UD and AD, it is noted that the productivity of workers in the case of AD increases by 50% than the productivity of workers in the case of UD as shown in Table. 15.

C. The effect of error on workstation

In Fig. 14 it has been observed that errors directly affect the number of work stations, and the reason is that the large number of errors increases the time for disassembly tasks, which increases the number of work stations because some workers are unable to do some disassembly tasks, which requires transferring them to the following work stations, and when comparing between UD and AD it is noted that the work stations Work decreases in case of AD by 33.3% than workstations in case of UD .

D. The effect of error on idle time

In Fig. 13 it has been observed that errors directly affect idle time, and the reason is that many errors increase the time of disassembly due to workers neglecting the appropriate tool for disassembly joints or the sequence of disassembly arrangement, which increases idle time at work stations because some workers overlook some disassembly, which requires alot of time to do them, when comparing between UD and AD for multi objective it has been observed that , it is noted that the idle time in the case of AD is 77.8% less than the idle time in the work stations in the case of UD as shown in Table. IV.

E. Balancing multi objective

In Fig. 15 shows a bar chart for multi objective (f_1, f_2, f_3 , and (f_4) in both cases AD and UD, where productivity (F_1) increased by 34.48%, at almost equal number of workstations (F_2), decreasing the cycle time for removal parts in workstations, and decreasing errors in case of AD.

VI. ANALYSIS OF INVESTMENT

We looked at the expected investment over 10 years to compare the investment on AD and UD, estimated productivity, and so that both times saving and cost-saving in the disassembly line in both conditions. To increase of a productivity constitutes the main criterion to choose the optimal structural possibility for the production line, which allows to calculate the increase in the productivity of the line, change the total costs and investment expenses, by reducing the quantity of workers on the line and the work period. In order to correctly determine the quantity of sectors, it is necessary to perform a comparison of the parameters of AD line and manual line consisting of the same workstations. It is possible to obtain sufficient accuracy during the calculation taking into account the following assumptions:

- 1) The workstations in the AD are the same, the loss times on all workstations are equal;

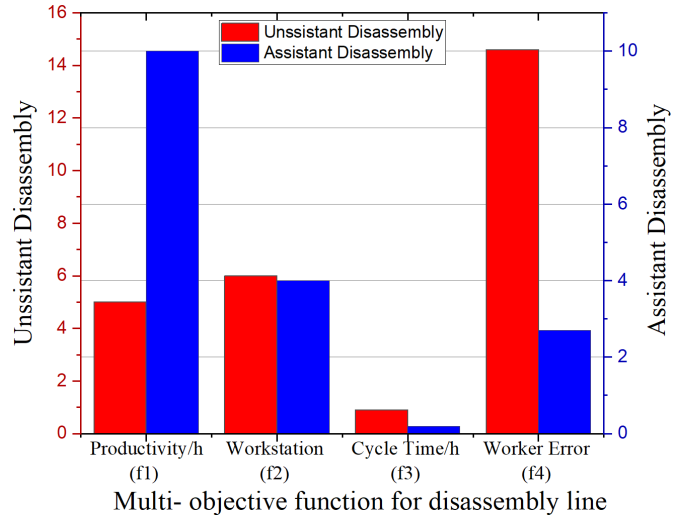


Fig. 15. The comparison of f_1, f_2, f_3 , and f_4 in case of UD, and AD.

- 2) The storage and feeding operations between the processes in the manual line allow to a void the mutual relationship between the workstations, while in the UD line with the rigid line, the failure of any work station leads to the suspension of the other of the workstations;
- 3) The costs on AD line are not related to the quantity of workstations. The rate of work productivity λ increase in the flow line compared to the AD line is determined by an equation (11)

A. Analysis of investment of UD

As for the UD disassembly line, according to the studied instance for waste products disassembly line, it needs 20 workers for 20 workstations (depending on the work stations) and 4 supervisors. The average monthly wage for the worker is \$1000, and the supervisor \$1600, through two shifts per day, and the total expenses are $T_{cost} = (1000 \times 20 + 1600 \times 4) \times 2 \times 12 = \$633,600$. The ideal structure for disassembly line to remove various types of damaged and out of date devices and equipment, the investment of this line is 10 years, with balancing factor is $B = 0.02$.

B. Analysis of investment of AD

The value of all disassembly workstation machines included in the disassembly line, workers and supervisors, the average monthly wages for the two operators are \$ 8000 for 20 workstations, and the one supervisor \$ 6000. $T_{cost} = (4000 \times 2 + 6000) \times 3 \times 12 = 336,000\$$. Average cost of added AD in workstation $M = 336,000/20 = 16,800\$$. Total expenses for one workstation include the following: The price of the carrier is \$ 15,000, AD system components are \$ 4,000, AD program connection between workstations is \$ 4,500, and additional expenses on equipment and equipment are \$ 4,000, and the total cost is \$ 27,500. The coefficient of the relative value of AD equipment and means with respect to the average value of the operating machine is equal to $\alpha = \frac{336,000}{16,800} = 20$. Current expenditures on operating and

TABLE II

NUMBER OF DISASSEMBLY ERRORS ENCOUNTERED IN DISASSEMBLY USING THE ASSISTANCE SYSTEM AND WITHOUT USING THE ASSISTANCE SYSTEM. THE ERRORS ARE ACCUMULATED FOR SIX DISASSEMBLY PRODUCTS TO SHOW THE POTENTIAL TRAINING EFFECT DURING DISASSEMBLY

Error type	(1-5)			(6-10)			(11-15)			(16-20)			(21-25)			(26-30)		
	UD	AD	G	UD	AD	G	UD	AD	G	UD	AD	G	UD	AD	G	UD	AD	G
Error(1)	20	11	F	16	9	M	10	4	F	6	3	M	4	2	F	3	2	F
Error(2)	16	10	M	10	5	F	7	3	M	6	2	F	2	1	M	2	2	M
Error(3)	17	8	F	6	4	M	3	1	F	5	1	M	1	0	F	1	1	F
Error(4)	19	4	M	4	2	F	2	0	M	1	0	F	0	0	M	0	0	F
Error(5)	4	3	M	3	1	F	0	0	M	0	0	F	0	0	M	0	0	M
Max	20	11		16	9		10	4		6	3		4	2		3	2	M
Mean	15.2	7.2		7.8	4.2		4.4	1.6		3.6	1.2		1.4	0.6		1.2	1	F
Min	4	3		3	1		0	0		0	0		0	0		0	0	F

TABLE III

STATISTICALLY COMPARISON OF SIX ERROR GROUPS BETWEEN UNASSISTED DISASSEMBLY AND ASSISTED DISASSEMBLY

Range of Disassembly	Unssistant Disassembly	Assistant Disassembly	Mean	Standard Deviation	SE of mean	Lower 95% CI of Mean	Upper 95% CI of Mean	Variance	Coefficient of Variation
1-5	20	15	17.5	3.53553	2.5	-14.2655	49.26551	12.5	0.20203
6-10	15	8	11.5	4.94975	3.5	-32.9717	55.97172	24.5	0.43041
11-15	10	5	7.5	3.53553	2.5	-24.2655	39.26551	12.5	0.4714
16-20	9	3	6	4.24264	3	-32.1186	44.11861	18	0.70711
21-25	7	2	4.5	3.53553	2.5	-27.2655	36.26551	12.5	0.78567
26-30	6	2	4	2.82843	2	-21.4124	29.41241	8	0.70711

TABLE IV

NUMBER OF DISASSEMBLY ERRORS PER CATEGORY SUMMED FOR ALL 10 DISASSEMBLY PRODUCTS PER TEST PERSON. THE FOUR CATEGORIES ARE ERRORS BY PRIORITY (EP), EXECUTION ERRORS (EX), ERRORS BY OMISSION (EO) AND QUANTITATIVE ERRORS (QE), (G) REFERS TO GENDER OF WORKERS; (F) IS FEMALE; AND (M) IS MALE.

Worker	Priority error (EP)			Execution Error(EX)			Error of Omission(EO)			Quantitative error(EQ)		
	UD	AD	G	UD	AD	G	UD	AD	G	UD	AD	G
Worker(1)	17	3	F	7	1	F	6	2	F	29	20	F
Worker(2)	16	1	M	7	2	M	6	2	M	28	20	M
Worker(3)	10	3	F	10	3	F	5	2	F	12	36	F
Worker(4)	19	3	M	15	2	M	4	2	M	19	20	M
Worker(5)	10	1	M	13	2	M	7	1	M	28	37	M
Worker(6)	13	5	F	15	1	F	6	2	F	13	34	F
Worker(7)	18	1	M	14	1	M	5	1	M	23	17	M
Worker(8)	17	4	F	14	3	F	5	1	F	27	34	F
Worker(9)	10	2	M	7	3	M	6	1	M	20	37	M
Worker(10)	16	4	F	8	1	F	8	2	F	26	36	F

TABLE V

STATISTICALLY COMPARISON OF ERRORS BETWEEN UNASSISTED DISASSEMBLY AND ASSISTED DISASSEMBLY

Type of error	Unassisted Disassembly				Assisted Disassembly			
	Mean	Minimum	Median	Maximum	Mean	Minimum	Median	Maximum
Priority Error (EP)	14.6	10	16	19	2.7	1	3	5
Execution Error (EX)	11	7	11.5	15	1.9	1	2	3
Error of Omission (EO)	5.8	4	6	8	1.6	1	2	2
Quantitative Error (EQ)	22.5	12	24.5	29	29.1	17	34	37
Average	13.475	8.25	14.5	17.75	8.825	5	10.25	11.75

TABLE VI
STATISTICALLY COMPARISON OF FOUR OBJECTIVES TO BALANCE DISASSEMBLY LINE, BETWEEN UNASSISTED DISASSEMBLY AND ASSISTED DISASSEMBLY

Objective functions	Unassisted Disassembly				Assisted Disassembly			
	Mean	Minimum	Median	Maximum	Mean	Minimum	Median	Maximum
Worker Productivity (f1)	5	3	5	7	10	9	10	11
Workstation (f2)	6	5	6	7	4	3	4	5
idle Time /hour(f3)	0.9	0.9	0.9	0.9	0.2	0.1	0.2	0.3
Worker Error (f4)	14.6	11	5.8	22.5	2.7	1.9	1.6	29.1

investing the disassembly line consist of expenditures on ongoing repair and technical maintenance, and expenditures for electrical removing tools, and for the case studied, the maintenance and repair expenditures per year are up to \$ 20,000, and the electric energy expenditures are \$ 5,000, so the total of these expenditures is $T_{v,l} = 25000$. The results obtained allow to determine the values of the economic and technical indicators necessary for the ideal structure of the disassembly line. Technical processing plant of the serial line is: $K = \frac{T_{runningcost}}{T_{workstationcost}} = \frac{1,235,520}{633,600} = 1.95$ The value of the m parameter for cost ratio : $m = \frac{T_{investment}}{T_{workerscost}} = \frac{25000}{633,600} = 0.04$. Factor for reducing expenditures on human effort is $\epsilon = \frac{\frac{1000 + \frac{1600}{1}}{1600}}{\frac{1600}{1600}} = 1.3125$ The periodicity of work stations in the AD disassembly line is approximately equal to the periodicity of the serial line $j = 1$. By substituting the values of all the parameters in the relation 7 and 8, the ideal number of work stations is determined, which it is useful to collect in an AD disassembly line to obtain a maximum increase in work productivity $W_{max} = \sqrt{\frac{3.34}{0.03} \times \frac{(1.95+10 \times 0.04)}{1.95+10(0.04+\frac{1}{1.3125})}} = 15$ workstations. The resulting W_{max} value allows for the coupling of the structure of the automatic line consisting of 15 workstations, in this case the largest increase in work productivity is reached compared to the traditional manual line, which is according to the relationship: $\lambda = 1 \times \frac{1+0.03}{1+0.03 \times 10} \times \frac{1.95+10(0.04+1)}{1.95+10 \times 0.22(1+\frac{20}{10}+\frac{10}{1.3125})} = 1.45$ According to equation 11 $\lambda = \frac{Q_2}{Q_1}$, thus $Q_2 = Q_1 \times \lambda$, $Q_2 = 1.45Q_1$, that is means the productivity after assistance model(AD) was increased by 0.45% from productivity before assistance model (UD).

VII. CONCLUSION

In order to determine how successful a sophisticated disassembly aid system is in preventing mistakes, this paper focuses on the condition of disassembly line in the actual world.

- Deep learning and the most current developments in disassembly aid systems are combined in the strategy that was chosen. Our suggested solution makes use of a deep learning object recognition model to precisely identify each disassembly item in real time. Other utilities, including system tools, get information from the item discovery module.
- A total of 34 tasks step for washing machine were disassembled using various disassembly techniques in order to assess the system's capacity to prevent errors. In tests with test subjects,

- the proposed assistance system was found to prevent 81.5 percent of errors when compared to a control group that did not use assistance.
- The system supervises the disassembly process and records that the components are not disassembled, preventing errors due to omission.
- This case study can also be representative of other similar assistance systems and sophisticated equipment due to the number of persons examined, the number of individual components, and the range of disassembly approaches. Additionally, it is shown how to utilize the collected data as significant information sources.
- The economic value of adopting the proposed support systems is still unknown, despite their high ability to prevent errors. A case-based analysis must be performed to estimate this value, which includes the cost of individual errors, personnel expenditures, and the value of extra transparency.
- Although the test subjects were unconcerned, the system's acceptability and usability in a production context require further investigation. Legal aspects should be clarified depending on local regulations, in addition to implementation details for use in the environment.
- The time-saving potential of the disassembly of proposed model can be examined in follow-up studies, and means to estimate its economic benefits can be discovered, and productivity was increased 0.45% after using assistance model.

DECLARATION OF INTEREST STATEMENT

The authors state that they have no possible consideration ambivalence, and no potential conflicts of interest.

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REFERENCES

- [1] C. B. Kalayci and S. M. Gupta, "Artificial bee colony algorithm for solving sequence-dependent disassembly line balancing problem," *Expert Systems with Applications*, vol. 40, no. 18, pp. 7231–7241, 2013.

- [2] E. KONGAR and S. M. GUPTA, "A multi-criteria decision making approach for disassembly-to-order systems," *Journal of Electronics Manufacturing*, vol. 11, no. 02, pp. 171–183, 2002.
- [3] N. Siddig, Z. Zhang, A. Mokhtar, and A. Abualnor, "Optimizing disassembly line balancing problem using multi-objective adam optimizer algorithm," *Journal of Karary University for Engineering and Science*, 2021.
- [4] A. Nadir, Z. Z. Qiang, A. Mokhtar, and A. B. Abualnor, "A hybrid genetic-adam optimizer to improve disassembly line balancing problem," *Journal of Karary University for Engineering and Science*, 2022.
- [5] H. Krikke, A. van Harten, and P. C. Schuur, "On a medium term product recovery and disposal strategy for durable assembly products," *International Journal of production research*, vol. 36, no. 1, pp. 111–140, 1998.
- [6] H. Krikke, A. van Harten, and P. Schuur, "Business case oce: reverse logistic network re-design for copiers," *Or-Spektrum*, vol. 21, no. 3, pp. 381–409, 1999.
- [7] E. Zussman, A. Kriwet, and G. Seliger, "Disassembly-oriented assessment methodology to support design for recycling," *CIRP annals*, vol. 43, no. 1, pp. 9–14, 1994.
- [8] Y. Feng, Y. Gao, G. Tian, Z. Li, H. Hu, and H. Zheng, "Flexible process planning and end-of-life decision-making for product recovery optimization based on hybrid disassembly," *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 1, pp. 311–326, 2018.
- [9] G. Boothroyd and L. Altling, "Design for assembly and disassembly," *CIRP annals*, vol. 41, no. 2, pp. 625–636, 1992.
- [10] M. A. Ilgin and S. M. Gupta, "Evaluating the impact of sensor-embedded products on the performance of an air conditioner disassembly line," *The International Journal of Advanced Manufacturing Technology*, vol. 53, no. 9, pp. 1199–1216, 2011.
- [11] K. E. Moore, A. Güngör, and S. M. Gupta, "Petri net approach to disassembly process planning for products with complex and/or precedence relationships," *European Journal of Operational Research*, vol. 135, no. 2, pp. 428–449, 2001.
- [12] F. T. Altekin, L. Kandiller, and N. E. Ozdemirel, "Profit-oriented disassembly-line balancing," *International Journal of Production Research*, vol. 46, no. 10, pp. 2675–2693, 2008.
- [13] S. M. McGovern and S. M. Gupta, "A balancing method and genetic algorithm for disassembly line balancing," *European journal of operational research*, vol. 179, no. 3, pp. 692–708, 2007.
- [14] A. Gungor and S. M. Gupta, "A solution approach to the disassembly line balancing problem in the presence of task failures," *International journal of production research*, vol. 39, no. 7, pp. 1427–1467, 2001.
- [15] A. Güngör and S. M. Gupta, "Disassembly line in product recovery," *International Journal of Production Research*, vol. 40, no. 11, pp. 2569–2589, 2002.
- [16] N. A. S. Ibrahim *et al.*, "Rehabilitation of the control unit of the cnc milling machine: Model f-v0-a2f," Ph.D. dissertation, Sudan University of Science and Technology, 2010.
- [17] A. Saleh, M. Sheaves, and M. R. Azghadi, "Computer vision and deep learning for fish classification in underwater habitats: A survey," *arXiv preprint arXiv:2203.06951*, 2022.
- [18] A. M. Obeso, J. Benois-Pineau, M. S. G. Vázquez, and A. Á. R. Acosta, "Visual vs internal attention mechanisms in deep neural networks for image classification and object detection," *Pattern Recognition*, vol. 123, p. 108411, 2022.
- [19] J. Yang, R. Xu, Z. Qi, and Y. Shi, "Visual anomaly detection for images: A systematic survey," *Procedia Computer Science*, vol. 199, pp. 471–478, 2022.
- [20] S. S. A. Zaidi, M. S. Ansari, A. Aslam, N. Kanwal, M. Asghar, and B. Lee, "A survey of modern deep learning based object detection models," *Digital Signal Processing*, p. 103514, 2022.
- [21] M. Sonka, V. Hlavac, and R. Boyle, *Image processing, analysis, and machine vision*. Cengage Learning, 2014.
- [22] S. Van der Walt, J. L. Schönberger, J. Nunez-Iglesias, F. Boulogne, J. D. Warner, N. Yager, E. Gouillart, and T. Yu, "scikit-image: image processing in python," *PeerJ*, vol. 2, p. e453, 2014.
- [23] S. Shakya *et al.*, "Analysis of artificial intelligence based image classification techniques," *Journal of Innovative Image Processing (JIIP)*, vol. 2, no. 01, pp. 44–54, 2020.
- [24] K. Rokni, A. Ahmad, K. Solaimani, and S. Hazini, "A new approach for surface water change detection: Integration of pixel level image fusion and image classification techniques," *International Journal of Applied Earth Observation and Geoinformation*, vol. 34, pp. 226–234, 2015.
- [25] P. F. Felzenszwalb, "Learning models for object recognition," in *Proceedings of the 2001 IEEE Computer Society Conference on Computer*

Vision and Pattern Recognition. CVPR 2001, vol. 1. IEEE, 2001, pp. I–I.

- [26] Z. Zou, Z. Shi, Y. Guo, and J. Ye, "Object detection in 20 years: A survey," *arXiv preprint arXiv:1905.05055*, 2019.
- [27] Y. Yang and D. Ramanan, "Articulated pose estimation with flexible mixtures-of-parts," in *CVPR 2011*. IEEE, 2011, pp. 1385–1392.
- [28] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "Yolov4: Optimal speed and accuracy of object detection," *arXiv preprint arXiv:2004.10934*, 2020.



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