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REVISTA LATINO-AMERICANA DE INOVAÇÃO E ENGENHARIA DE PRODUÇÃO

DEPLOYMENT OF A VISION SENSOR AND AN EXPERT SYSTEM TO MINIMIZE PLASTIC WASTE: A CASE STUDY IN COLORED OPTICAL TUBES EXTRUSION

DESPLIEGUE DE UN SENSOR DE VISIÓN Y SISTEMA EXPERTO PARA MINIMIZAR RESIDUOS PLÁSTICOS: UN ESTUDIO DE CASO EN EXTRUSIÓN DE TUBOS ÓPTICOS COLORIDOS

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Received: 25 February 2024 / Accepted: 20 March 2024 / Published: 31 March 2024

ABSTRACT. Industry 4.0 has expanded the alternatives to design more sustainable processes. Among the technologies of this industrial phase, IoT (Internet of Things) technology allows the linkage of devices that generate data at high volumes (big data), supporting the creation of Artificial Intelligence (AI) models to perform optimal operating standards to minimize waste in the production. By means of vision sensor and AI deployment, this study aimed to reduce the polybutylene plastic waste in an extrusion line of colored tubes, in which most of the waste is generated during the color transition. For that, a vision sensor that transfers the tube color in real-time was installed, which made it possible to set acceptance ranges for the standard colors of the tubes based on the elicitation of the operators' knowledge. These ranges allowed the setup of an expert system that warns the operator, by a light signal, the right time to start the production. The suggested technology demonstrated to be 11.47% more efficient in waste reduction in color transitions. It also allowed the identification of the requirements for the deployment of this technology in plastic extrusion, so it can promote overall waste reduction, which requires improvements in operation, standardization, and employee training.

Keywords: Cleaner Production, solid waste minimization, Industry 4.0, vision sensor, expert system

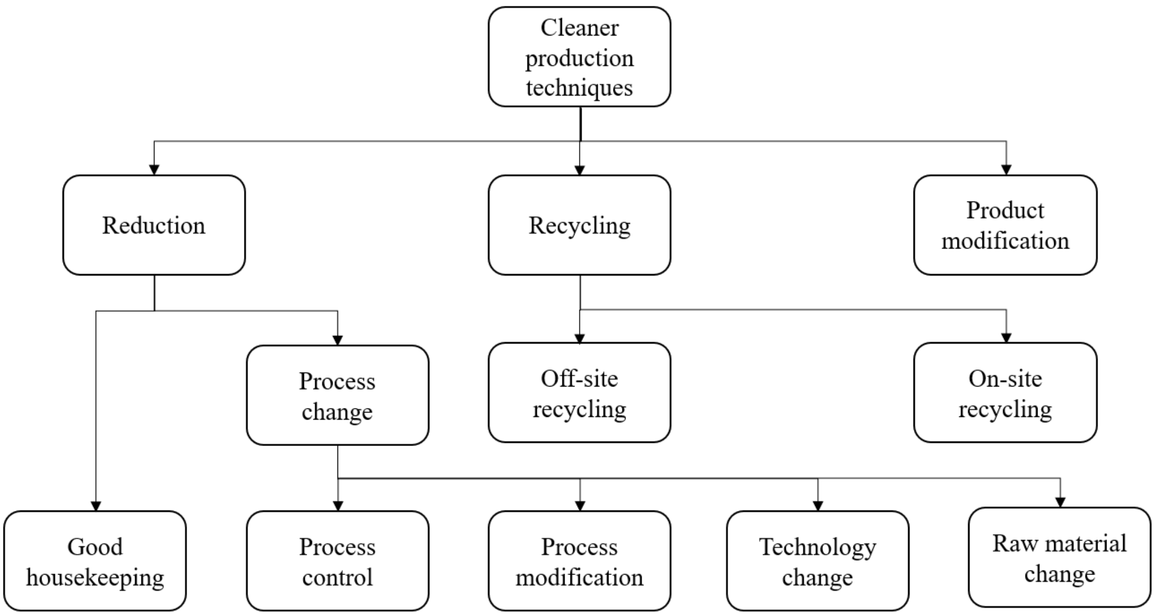
RESUMEN. La Industria 4.0 ha ampliado las alternativas para diseñar procesos más sostenibles. El IoT (Internet de las Cosas) permite vincular dispositivos que generan datos en grandes volúmenes (*big data*), apoyando la creación de Inteligencia Artificial (IA) para minimizar el desperdicio en la producción. Mediante el uso de sensores de visión e inteligencia artificial, este estudio tuvo como objetivo reducir los residuos plásticos de polibutileno en una línea de extrusión de tubos coloridos, donde la mayor parte de los residuos se generan durante la transición de color. Para ello, se instaló un sensor de visión que transfiere el color del tubo en tiempo real, lo que permitió establecer rangos de aceptación para los colores estándares de los tubos basándose en el conocimiento de los operadores. Estos rangos permitieron la configuración de un sistema experto que advierte al operador, mediante una señal luminosa, el momento adecuado para iniciar la producción. La tecnología sugerida demostró ser un 11,47% más eficiente en la reducción de residuos en las transiciones de color. También permitió identificar los requisitos para el despliegue de esta tecnología en la extrusión plástica, de modo que promueva la reducción general de residuos, con mejoras en la operación, estandarización y capacitación.

Palabras clave: Producción más Limpia, minimización de residuos sólidos, Industria 4.0, sensor de visión, sistema experto

1 INTRODUCTION

The minimization of the pollution in its source is a strategy that has been adopted since 1989 under the name of Cleaner Production (CP), a concept introduced by the United Nations Environmental Programme. The discussion evolved in the following years and CP was adopted in United Nations Agenda 21 in 1992 as a strategy to reconcile the need for environmental protection with economic development (UNEP, 2002). The adherence of this approach with the principles of Lean Manufacturing (Oliveira, 2016) reinforces the economic and environmental benefits of the reduction of waste in the operation, which made CP easily absorbed by industries that endorse techniques and methods developed by Toyota in the post-war period. El-Haggar (2007) describes the core CP techniques that address the pollution in its source, preventing its production “before-the-event”. Such techniques are deployed from three main branches of action: Reduction, Recycling and Product Modification (FIGURE 1).

FIGURE 1. CLEANER PRODUCTION (CP) TECHNIQUES



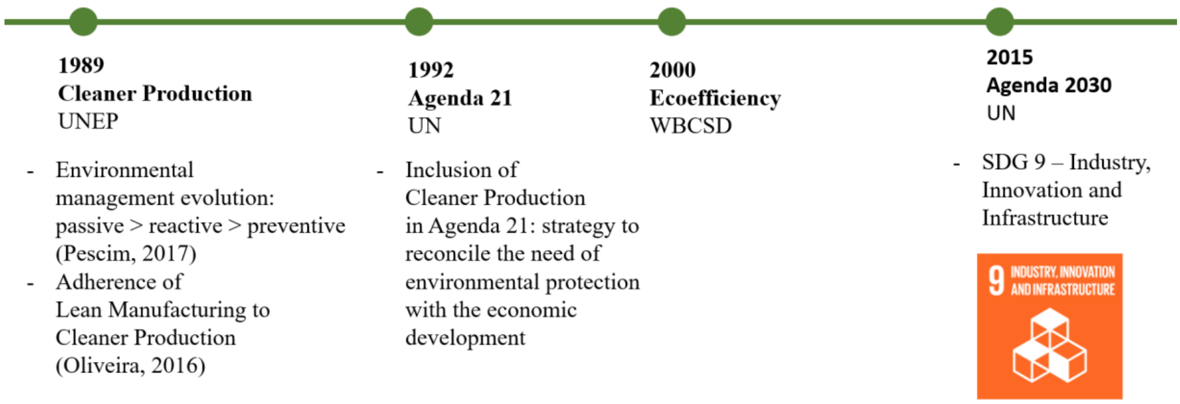
SOURCE: EL-HAGGAR (2007)

A survey with Brazilian industry professionals identified that organizational factors are crucial for a successful CP application, where including CP principles in strategic planning and a strong continuous improvement culture appear as the most relevant factors

(Vieira & Amaral, 2017). Pescim (2017) describes the evolution of environmental management in the organizations from passive to reactive and, finally, the preventive approach, in which the CP appears as a productive strategy appropriate to the need to prevent the pollution in source.

In the first decade of the XXI century, the concept of Ecoefficiency also gained notoriety through the World Business Council for Sustainable Development report (WBCSD, 2002), by outlining the economic objectives of the rational use of natural resources, which results in environmental benefits. Except for slight differences, both terms (Ecoefficiency and CP) converge to productive approaches that aim to minimize the pollution in the source. Later in 2015, the concept of CP (FIGURE 2) is resumed in the Sustainable Development Goal (SDG) 9 of Agenda 2030 of the United Nations, which claims to upgrade infrastructure to increase resource-use efficiency as well as adopt clean and environmentally sound technologies and industrial processes (United Nations, 2015).

FIGURE 2. TIMELINE OF ENVIRONMENTAL MANAGEMENT MILESTONES SINCE CLEANER PRODUCTION (CP) INTRODUCTION



SOURCE: The authors (2024).

Simultaneously to the increasing global concern on environmental protection, the industrial production model reaches its fourth stage, the so-called Industry 4.0. It consists of a group of technologies, devices, and processes able to operate in an integrated manner throughout the several phases of the productive process as well as the different levels of the supply chain (Castelo-Branco et al., 2019). Stock and Seliger (2016) describe its main levers as electronic and information technology advancements, which allow the realization of a high level of automation in production. Such innovations support the optimization of processes while contributing positively to the more efficient use of resources and to the reduction of waste in production (Kiel et al., 2017).

Inside of Industry 4.0 toolbox, Ardanza et al. (2019) emphasize the important role that the Internet of Things (IoT) protocols play in capturing and transmitting a great amount of data to cloud servers to support decisions that promote process improvements. Dogan and Birant (2021) describe modern factories where sensors send data in real-time, enabling triggers in machines that will learn through Artificial Intelligence (AI) how to respond autonomously to process conditions that generate excessive waste or affect product quality requirements such as shapes and colors.

Zhao et al. (2022) introduce the inspection of product appearance as a crucial activity in determining quality in industrial manufacturing, since the appearance can be related to the assembly status of parts or geometric dimensions that affect its functionalities. In this context, Zhao et al. (2022) describe the widespread use of detection methods in which it is not necessary to touch the parts or products inspected, being widely applied in the industrial automation field due to the possibility of substituting humans in the accomplishment of certain tasks, increasing efficiency and reducing cost.

Computer-based vision systems have been used in industry for product inspection since the 80's (Ullah et al., 2021) by means of the photogrammetry technique, which consists of extracting from photos the shape, dimensions, and position of objects. Since the successful deployment of convolutional neural networks (Krizhevsky et al., 2012) for the development of AI able to differentiate with precision the conformity of products from digital images, this field of study has obtained great advancement in recognizing patterns, demonstrating the great potential of vision technologies expansion (Zhao et al., 2022). According to Ullah et al. (2021), computer-based vision systems can provide real-time information about the conformance or non-conformance of manufactured products, which can be used to adjust parameters in the process with the objective of minimizing defects.

Li et al. (2018) have analyzed the use of a defects inspection system in assembly lines, setting cameras in production in combination with AI to identify defects. Ullah et al. (2021) proposed, on the other hand, a low-cost system to be applied in small and medium enterprises (SMEs) in emerging countries, with the use of IoT protocols that send images to cloud servers. These images were accessed by monitoring centers to assess in real-time whether a product meets or not the quality requirements.

Color is one of the features of a product that may be under process control and colorimetry is widely used in the food industry due to the relevance of color in food quality. Studies on toasted rice (Nguyen et al., 2022), vine tomato coloring (Roy et al., 2017), and pre-cooked sausages (Feng et al., 2017) demonstrate the application of colorimetry on quality inspection. Nguyen et al. (2022) highlight important aspects in the application of colorimetry in computer-based vision systems, such as the transformation of color models to treat color numeric data and the proximity of the camera from the object to ensure homogenous light.

The inspection of product features such as color is being progressively executed by AI models, such as expert systems (ES). An ES consists of a logical structure able to make complex decisions based mostly on conditional rules, presenting as main components a Knowledge Base and an Inference Engine (Kaur, 2018). According to Tolun and Oztoprak (2016), an ES must be built using the experience of an expert in a particular knowledge domain by means of knowledge elicitation techniques, which consists of translating the human expertise into objective functions that can be coded in an algorithm.

2 METHOD

Combining the CP and SDG 9 approaches with the context of Industry 4.0 described by Stock and Seliger (2016), it is possible to identify a myriad of technologies to make operations cleaner and more efficient. Using a vision sensor and an expert system (ES), this study aims to deploy this technology to minimize the waste in the color transition operation in the plastic extrusion of optical colored tubes. This trial was executed as a case study in an optical tube extrusion line, where a single extrusion machine generated 2,892 kg of waste during the tubes color transition in 5 months from August 2021 to March 2022.

First step: Color standard description

This step consisted of describing the color standard for optical tubes adopted in the factory of this study. The ES was set based on this standard.

Second step: Color transition operation analysis

The color transition operation was first analyzed as part of the plastic material flow in the extruding machine. Secondly, this operation was interpreted in terms of the length and speed variation throughout optical tube production. And finally, the color transition was investigated from the operator’s work perspective, identifying the activities in which the tube waste is generated.

Third step: Tube waste measurement

For technology efficacy measurement, it was set an indicator for the tube waste in preparation cycles. The calculation of this indicator was based on the current length (L_i) and linear speed (V_i) data collected at every timestamp (i) registered in the extruding machine controller. Both parameters (L_i and V_i) vary according to the tube production or preparation, hence the L_i is reset anytime it alternates from production to preparation cycles and vice versa, resulting in a cycle (C_i) length calculation (Equations 1 and 2).

$$\boldsymbol{For\ L_i \leq L_{i+1} :\ C_i = 0} \qquad (1)$$
$$\boldsymbol{For\ L_i > L_{i+1} :\ C_i = L_i} \qquad (2)$$

Where:

L_i = current length

V_i = current linear speed

C_i = production or preparation cycle length

The data has been collected during an interval of 8 months of the extruding machine operation and undertook an outlier removal process (Kassambra, 2023). The analysis resulted in an average tube waste per cycle that served as baseline for the previous technology setting.

Fourth step: Vision sensor installation

Considering the particularities and restrictions of the color transition operation and environment, this step consisted of installing the vision sensor to ensure a consistent and reliable color data collection. The device selected was an RGB camera that displays color data in hue, saturation, and value (HSV) model.

Fifth step: Expert system setting

The Expert System had as its knowledge database the HSV ranges of the 12 standard colors for the tubes. To allow the setting of the right color standard, it was distributed to the operators a check sheet in which they were entitled to register the tube color and the time they recognized the color standard compliance. The records were cross-referenced with the HSV data collected at the exact same time from the RGB camera, which made it possible to define the acceptable range of Hue (H), Saturation (S), and Value or Bright (V) parameters for each color.

The ES inference engine consisted of a conditional command coded in C language algorithm block (Surek, 2022) in extruding machine controller to assess the HSV data collected in real time. The digital response resulting from the comparison between the current color data of the tube with the knowledge database was converted into a light signal in the operation area, advising the operator about the right time to start the production.

Sixth step: Data analysis after technology deployment

The suggested technology remained in operation for 46 days. Adopting a 95% confidence interval in Kassamba (2023) t-test in R, the sample means from before and after technology deployment were statistically compared to produce a conclusion regarding the technology efficacy.

3 RESULTS

3.1 COLOR STANDARD DESCRIPTION

This study follows the ABNT (Associação Brasileira de Normas Técnicas – Brazilian Association of Technical Norms) norm to codify the color of the tubes in the optical cables. There is no single ABNT norm to describe exclusively the coding for the colors of tubes and fibers, but these specifications are embedded in the norms for manufacturing every optical cable according to its use.

In the case of multi-tube cables, this pattern allows the identification of the position of each fiber in each tube. It is useful for fitters that need to splice fibers during the installation of local area network (LAN) or wide area network (WAN), as well as for locating breaks or faults in the network. Therefore, the use of this norm is an essential requirement for product quality because it has adopted a recognized standard for optical cables color coding, which guarantees consumer acceptance.

The norm ABNT NBR 14160:2020 for dielectric self-sustaining aerial optical cable proposes 12 colors to differentiate tubes and fibers (CHART 1), including the use of marks to distinguish the fibers in tubes with more than twelve fibers.

CHART 1. COLOR CODING FOR TUBES AND OPTICAL FIBERS STANDARD

Position	**Color**
1	Green
2	Yellow
3	White or natural
4	Blue
5	Red
6	Violet
7	Brown
8	Pink
9	Black
10	Gray
11	Orange
12	Aqua

SOURCE: DESIGNED FROM ABNT NBR 14160:2020 (2020).

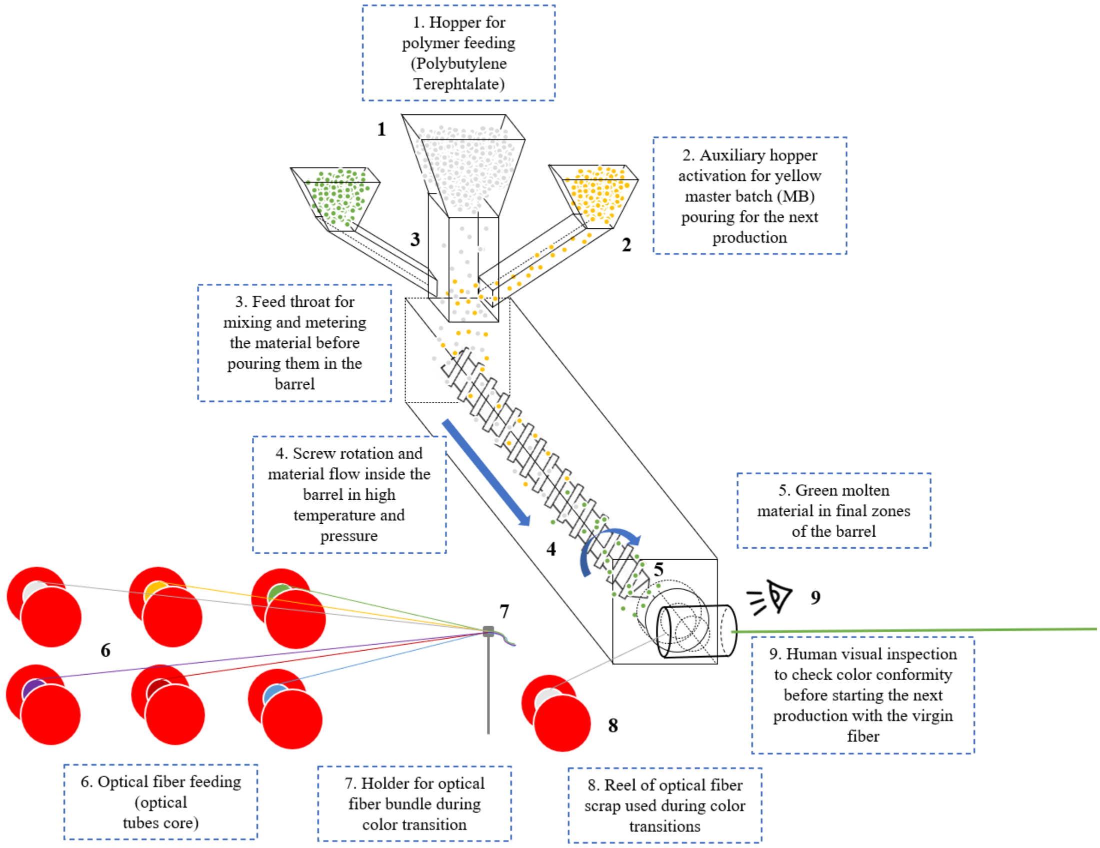
3.2 COLOR TRANSITION OPERATION ANALYSIS

The production of colored optical tubes happens in a plastic extrusion line, where one or more optical fibers are projected into a concentric cross-section that is extruded into an extended plastic profile. The whole tube extension is then winded onto reels to follow the next stages of the optical cable production.

The color transition happens when there is a shift from one color to another in an uninterrupted production sequence. Since the completion of a single batch of multi-tube cables requires the manufacturing of the whole color set of a specific order, it is not viable to group the production of the same color tubes from different batches under the risk of delaying the shipment. The color transition is then a constant operation in the optical tube extrusion production line, reaching an average of thirteen occurrences a day in a single machine.

For example, the color transition from green to yellow can be described in nine steps, naming each machine part that is relevant to comprehending the context of this intervention (FIGURE 3).

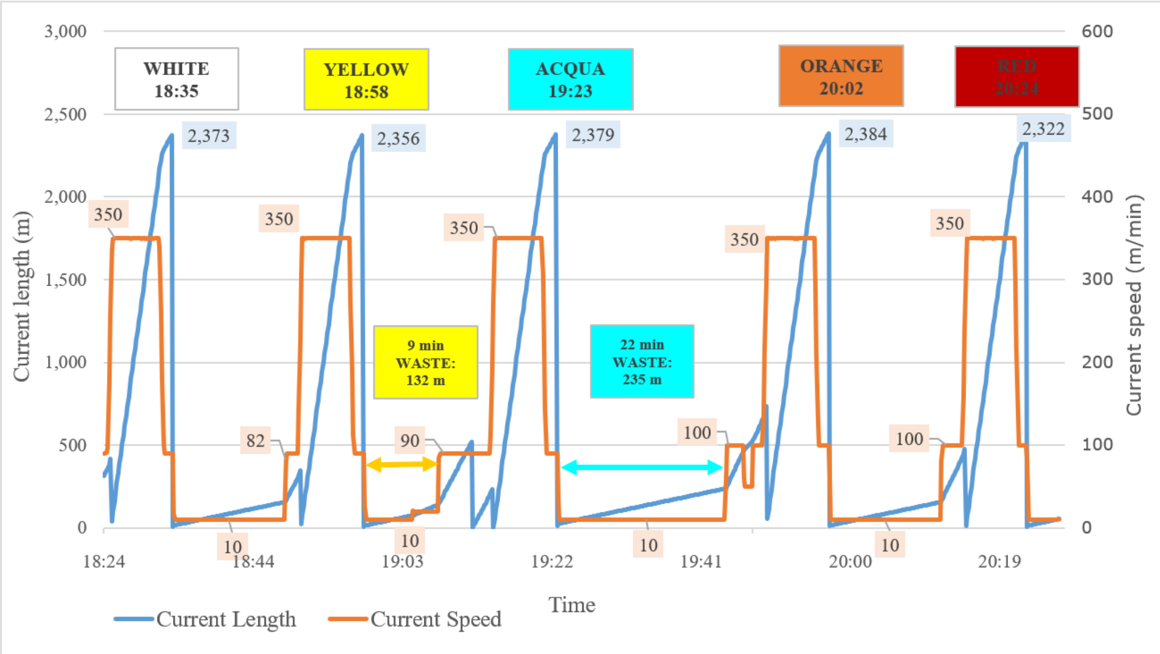
FIGURE 3. COLOR TRANSITION OF OPTICAL TUBE EXTRUSION STEP BY STEP



SOURCE: The authors (2024).

The start-up of the auxiliary hopper that pours the master batch (MB) in the barrel is triggered by an anticipation factor. This factor consists of a predefined length to determine a safe timing to pour the next color MB in the barrel, in such a way that it does not affect the color homogeneity of the tube in production. Once the length gauge reaches the anticipation factor, the auxiliary hopper pours the next color MB in the barrel. Invariably a certain length of tube will be produced in an intermediary color that is not acceptable for ABNT standards. This tube in non-standard color becomes waste. A tube batch production on 8th May 2020 demonstrates the exact moment of a color transition based on linear speed and tube length variation (FIGURE 4).

FIGURE 4. COLOR TRANSITION IN TERMS OF CURRENT LENGTH AND SPEED VARIATION



SOURCE: The authors (2024).

The interpretation of FIGURE 4 requires the understanding of the following aspects:

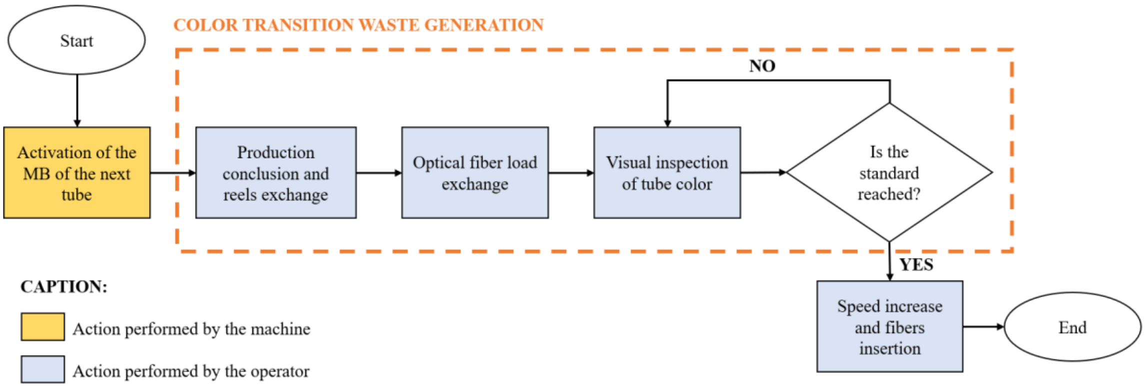
I. Reels length: the reels length varies among batches, reaching 2,384 meters in the given time interval. The shorter the reel length, the higher the number of color transitions between the production cycles.

II. Production and starting speed: to insert the optical fibers in the tube to start the production cycle, the operator must increase the screw rotation to a resulting linear speed of approximately 100 m/min. Thereafter, the speed rises to 350 m/min in production speed, forming a stairway shape of the orange line.

III. Length gauge reset: to calculate the produced reel length, the operator must reset the length gauge once the extrusion cycle reaches the production speed, promoting sharp drops in the blue line whenever the length reaches 0.

The color transition waste is generated during the time between the production peaks and the next starting speed. In these intervals, the operator executes operational tasks while checking the color change until the moment it reaches the standard, and it is ready for the next production cycle (FIGURE 5).

FIGURE 5. COLOR TRANSITION WASTE GENERATION FLOWCHART



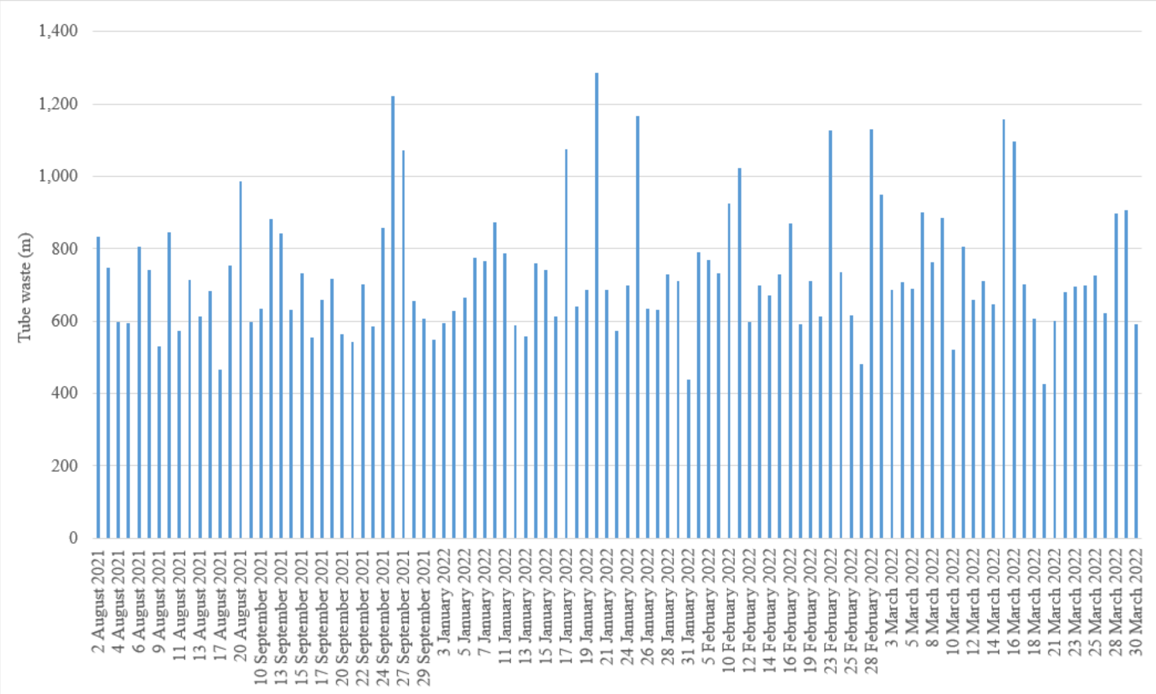
SOURCE: The authors (2024).

There was frequent time interval between the cycles when the tube color has already reached the standard, but the operator did not insert the fiber for the next production yet. This time interval of avoidable waste was attributed to the different perception of the operators on the color standard, which it is related to several factors such as experience in the process, environment light, and attention in the workplace.

3.3 WASTE GENERATION MEASUREMENT

To address the variability in human color perception, this trial planned and put in operation the technology of a vision sensor (RGB camera) combined with an ES to minimize the waste generated during the color transition. The efficacy of this solution was measured by the indicator of the daily average length lost in every preparation cycle (GRAPH 1).

GRAPH 1. DAILY AVERAGE LENGTH (METERS) OF TUBE WASTE IN EVERY PREPARATION CYCLE



SOURCE: The authors (2024).

The current linear speed results from the extrusion screw rotation rate, which is converted into a meters per minute rate by which the tube is projected from the die and runs along the cooling trough toward the payoff reel. If the current linear speed was equal to or higher than 230 m/min, the cycle length was classified as production, otherwise, it was preparation. The sample listed in Graph 1 were selected according to data availability, resulting in an average of 733.16 meters of tube waste in every preparation cycle during the period analyzed.

3.4 VISION SENSOR INSTALLATION

Based on the observation of the operator color perception during the color transitions, it was listed the requirements for the vision sensor installation to replicate this task.

I. The sensor must start the color recognition from the moment when the MB of the next production is poured in the cylinder, so the color data collected represents the whole transition phase.

II. The best place to install the sensor is next to the extruding die. For that, the device must tolerate high temperatures (up to 50ºC) and disturbances as steam and dust that emerge from the water trough.

III. The vision sensor installation must allow its displacement for cleaning and maintenance routines.

IV. The vision sensor must be resilient to eventual collisions, considering that the operators are constantly moving around the extruding die.

V. The vision sensor screening area must have a fixed light source, so the image collection can have a light standard for comparison.

The device installed was an RGB camera that displays the color data in hue, saturation, and value (HSV) model. The equipment tolerates temperatures above 50ºC, and it was installed along with a fixed light fixture to ensure the same light in every image taken. The vision sensor transferred the HSV color data through Ethernet cabling to the extruding machine PLC, which was connected to a gateway that communicates with an IoT industrial architecture that transfers huge amounts of data by Message Queuing Telemetry (MQTT) protocol. The data generated was then stored in a cloud server for further analysis.

Certain adjustments in camera settings and surroundings were executed to ensure the durability of the technology and the precision of the color data collected, as follow:

I. The camera collected the images directly from the tube cone, an area that emanates steam and particulate matter that can damage its lens. It was then built a chamber connected to the factory compressed air supply to create a positive pressure to expel these damaging vapors, so the camera remained enclosed and protected.

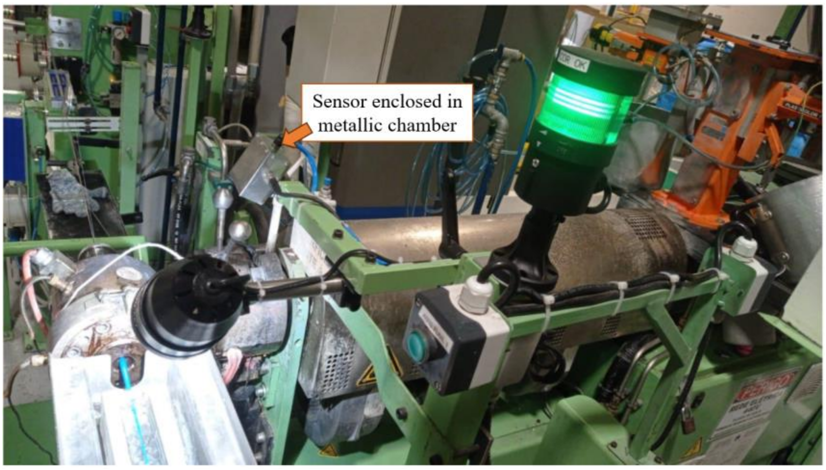
II. The synchronization of the shutter timer with the light fixture of 8.3 ms wave period (120 Hz frequency) to allow the homogeneity of the images taken, reducing the variation of saturation (S) and value (V) parameters.

III. The installation of a polarizing filter to neutralize the specular reflectance that distorts the brightness (V) measurement, especially in pink, white and aqua tube colors.

3.5 EXPERT SYSTEM SETTING

The Expert System compared the color data collected by the RGB camera with the knowledge database, providing a digital response that was converted into a light signal in the operation area. If the HSV color data registered lies between the set ranges, a green light beacon turns on (FIGURE 6).

FIGURE 6. LIGHT SIGNAL INDICATING THE COLOR CONFORMITY OF A BLUE TUBE IN PRODUCTION

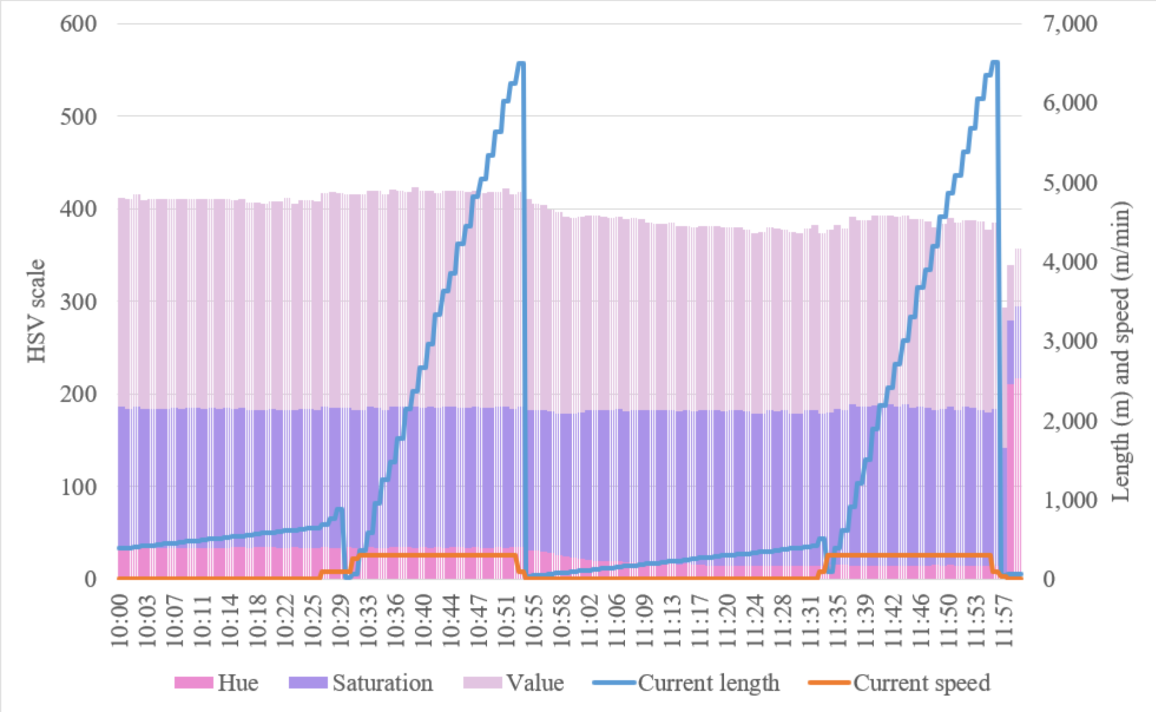


SOURCE: The authors (2024).

The light signal was then the command for the operator to start the next production, marking the moment when the tube had already reached its standard color. The tube expelled from the die formed a cone that shrunk once it passes through the water trough. The operators observed the color transition from this cone, the first area in extrusion line where the tube became visible. They inserted the virgin optical fiber to start the production whenever the color reached the acceptable standard.

To allow the setting of the right color standard, it was distributed to the operators a check sheet in which they were entitled to register the tube color and the time they recognized the color standard compliance. The records were cross-referenced with the HSV data collected at the exact same time as well as its maximum and minimum measurements (GRAPH 2). This made it possible to define the acceptable range of Hue (H), Saturation (S), and Value or Bright (V) parameters for each color. The setpoints representing each HSV parameter's maximum and minimum value were updated directly on the controller database through an Application Programming Interface (API). The list of these ranges (CHART 2) were used as the knowledge database for the ES.

GRAPH 2. DASHBOARD FOR A COLOR TRANSITION FROM YELLOW TO ORANGE ON JANUARY 12th 2023



SOURCE: The authors (2024).

CHART 2. HSV RANGES FOR TUBE COLOR STANDARDS

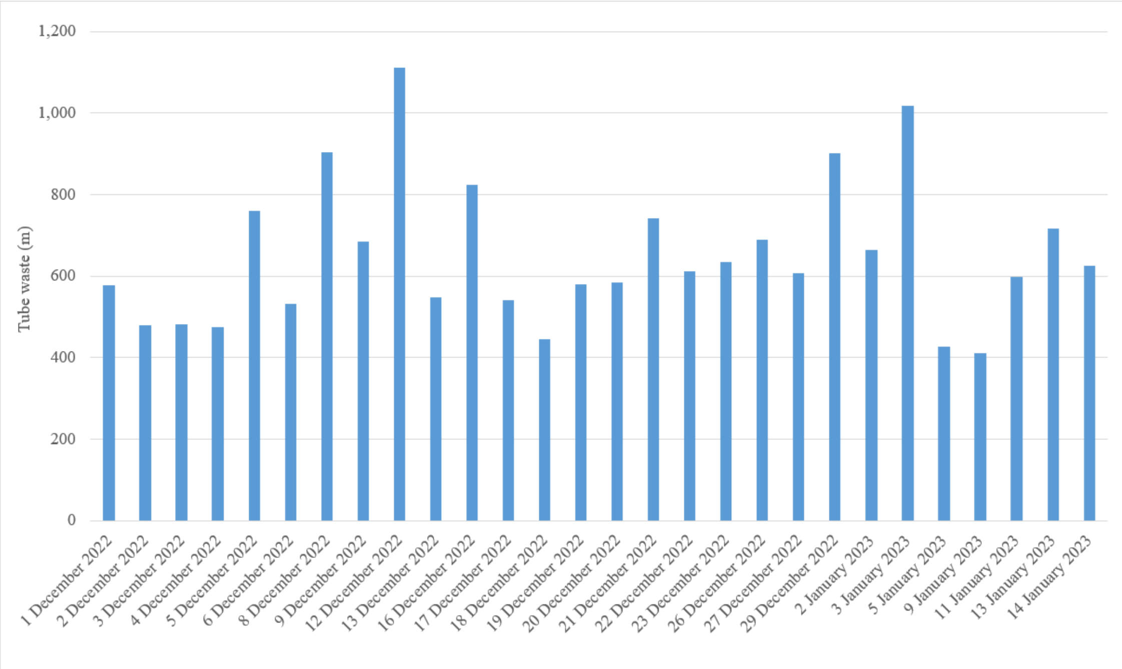
Color	H min	H max	S min	S max	V min	V max
Red	355	2	132	168	117	133
Orange	7	11	158	183	175	198
Maroon	341	4	49	95	90	97
Yellow	30	41	135	159	195	230
Green	149	177	92	144	87	107
Aqua	183	190	109	128	189	202
Blue	212	222	154	201	104	119
Violet	217	235	67	130	44	89
Pink	356	10	45	64	192	206
Gray	213	234	22	43	102	124
White	330	96	4	56	221	255
Black	208	232	55	104	61	81

SOURCE: The authors (2024).

3.6 DATA ANALYSIS AFTER TECHNOLOGY DEPLOYMENT

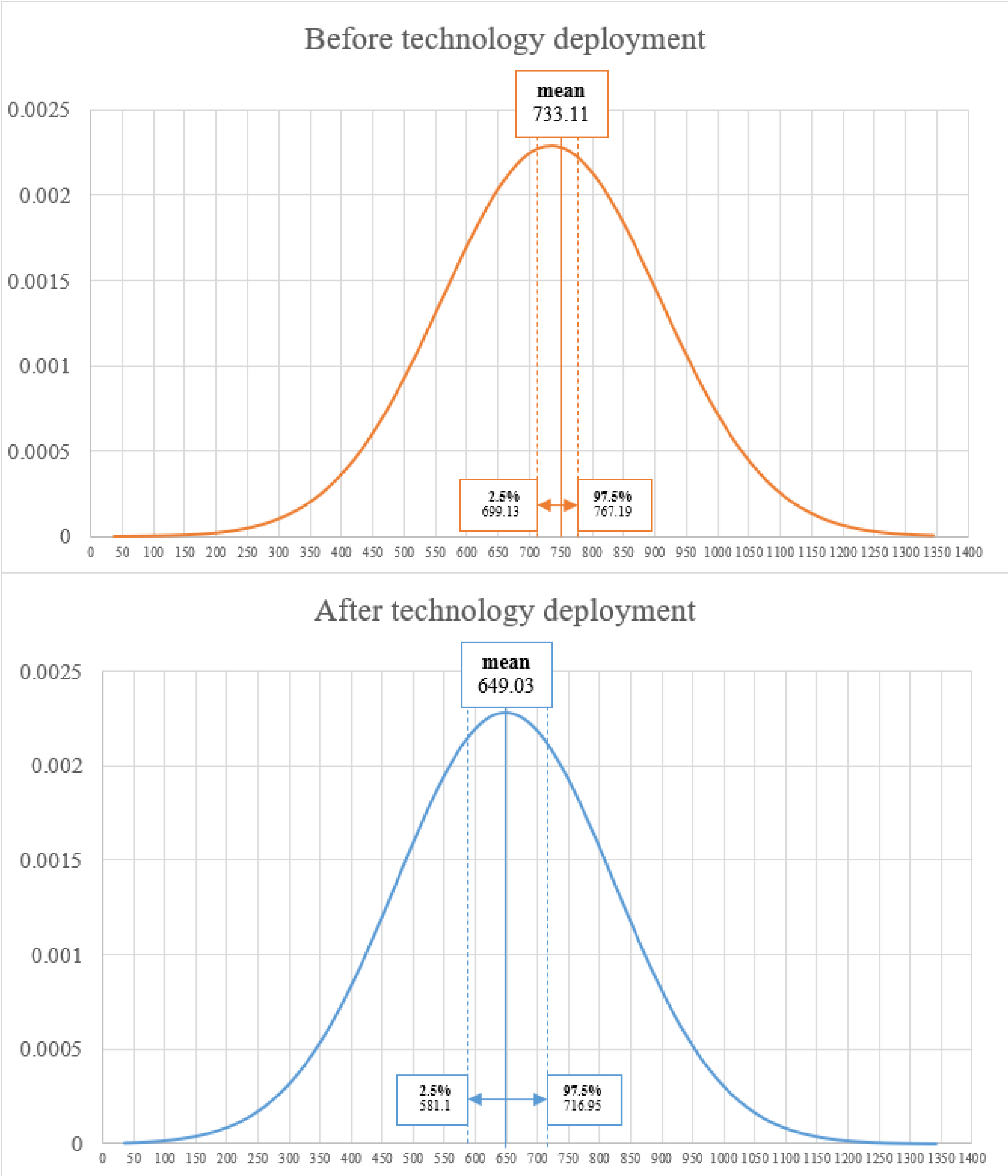
The suggested technology remained in operation for 46 days, and the result obtained after outliers removal process (GRAPH 3) presents an average tube waste of 649.03 m. Adopting a 95% confidence interval in Kassamba (2023) t-test in R (FIGURE 7) the sample means from before and after technology deployment are statistically different. Since the mean after technology deployment is lower, the new technology is 11.47% more efficient, with 95% of confidence.

GRAPH 3. DAILY AVERAGE LENGTH (METERS) OF TUBE WASTE IN EVERY PREPARATION CYCLE AFTER TECHNOLOGY DEPLOYMENT



SOURCE: The authors (2024).

FIGURE 7. BEFORE AND AFTER TECHNOLOGY DEPLOYMENT GAUSSIAN CURVES COMPARISON



SOURCE: The authors (2024).

4 DISCUSSION

The vision sensor combined with the ES advised the operators about the best time to start the production, which reduced the waste provoked by operators' color perception variability during color transitions. However, other unknown reasons hindered them to follow the light signal timing on every single occasion, which resulted in high overall tube waste rate. Throughout the spectrum of CP techniques, there were alternatives other than technology change to be explored before investing in expanding this technology. Good operating practices must be established to ensure that the operators themselves were able to reduce the waste in color transitions at first place.

As a requirement for the vision sensor and ES deployment, shopfloor management must exploit waste reduction techniques in workflow to design the cleanest color transition process possible. Once this operation is proven to be in its optimal settings, it is recommended to start the expansion of the vision sensor and ES technology to other machines.

In this case study, the following waste reduction techniques must be executed prior to the vision sensor and ES deployment:

I. Creation of a color transition operational decision tree to describe best practices to minimize waste in different circumstances.
II. Quantitative validation of the decision tree as an effective guide for waste reduction in tube color transition.
III. Operational procedure elaboration based on the validated decision tree.
IV. Employees training and periodic operational audits.

5 CONCLUSION

This work aimed to deploy vision sensor and AI to promote waste reduction in a colored tubes extrusion, contributing to the literature as a comprehensive case study presenting the implementation steps, challenges, and limitations of the technology. Further studies on this subject must consider a preparation setting for the vision sensor and ES deployment to ensure the overall waste reduction in tube extrusion, which involves fundamental techniques on CP.

The suggested technology demonstrated to be 11.47% more efficient in waste reduction in color transitions. However, the high overall waste rate in the case study extrusion line suggested that there are many other hidden factors that hindered the operator from starting the production after color transitions, despite being aware of the standard color accomplishment announced by the light signal. Such factors are connected to circumstantial settings of the operation itself, which must be mapped to address workflow causes that contribute to waste generation during color transition.

The technologies of Industry 4.0 have already demonstrated their potential to promote substantial improvements in sustainability in industrial settings. This study outlines the importance of analyzing the vast possibilities of people's behavior in operation before deploying technologies that substitute partially manpower, which can leverage or weaken the solution results according to the accuracy of this analysis.

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