RESEARCH PAPER

NextGen Vision-Based Sensor-Fusion Dynamic Distribution System

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ABSTRACT

Traditionally, conveyors controlled by PLCs have always been based on a simple sensor arrangement where only one sensory input was required for decision making, usually either weight measurement or light detection by means of an optical sensor. However, the use of such a simplistic arrangement poses some difficulties when it comes to variations in packages' size, mass, or lighting conditions in general because the sensor can provide false outputs, and the conveyor will route the package to the wrong chute. As a solution, the proposed design introduces a conveyor sorting system based on the combination of three different sensors, each providing its own output which the PLC combines according to predetermined rules to decide whether or not to initiate the diverting mechanism. The weighing of the package is performed at the point of entry to eliminate vibrations caused by the movement of the belt. The vision algorithm analyzes the image and detects the presence of an empty chute out of three possible options available, delivering the result as a vector of binary values to the PLC every 30 frames per second. The entire control loop, encompassing both image processing and input-output arbitration, operates completely within the PLC, devoid of any computing host outside the system. Performance validation via prototyping over six hundred packages through three controlled settings revealed a routing accuracy of 97.8%, actuation time invariably under 120 ms, and a 21% reduction in misrouting compared to a like system featuring a single sensor. This compares positively to previous systems that have been validated in hardware, even those utilizing deep learning, which are computationally heavier. This design is modular in structure; hence, expanding zones for deliveries or changing sensors necessitates merely local adjustments to the fusion table and PLC ladder logic.

Keywords: automated package distribution; industrial automation; Industry 4.0; multi-sensor fusion; programmable logic controller; vision-based slot detection

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1. INTRODUCTION

In terms of throughput data over the past ten years, conveyor sortation can be said to hold pride of place as the central component in any modern logistics facility. A single misplaced package or delay in chute routing leads to a ripple effect further down the chain, making it harder to keep the picking, packaging, and dispatch processes on schedule [1]–[3]. It has been commonplace practice since the late 1970s for a Programmable Logic Controller to handle the sortation process, and with good reason. The deterministic scanning cycles, immunity to electrical interference, and seamless connectivity with other industrial equipment are all characteristics that set controllers apart from desktop machines [4, 5]. The issue, then, is not the controller but its sensors..

The typical approach is to give the PLC one input only, be it from the weight sensor, the photoelectric gate, or the proximity switch, and expect the PLC to classify parcels that might vary in terms of weight, size, and even surface texture. This might be feasible under ideal circumstances where the parcels are uniform; however, real-world examples are such that a mechanical device weighing 15 kg may have the same effect on a vibrated belt scale as an envelope with a 0.3 kg circuit board. Moreover, the inability of the blocked photoelectric beam to differentiate between parcels and the maintenance staff moving through the assembly line causes misrouting. This problem accounts for a rate that, in most research studies, falls somewhere around 15–23% of packages classified wrongly [4, 6].

Recent research into machine vision [7, 8], sensor fusion [9], and even the general idea behind Industry 4.0 [10, 11] hints at a different paradigm for solving the problem: assign each sensor to a unique physical phenomenon that needs measuring, and then aggregate their results by means of some relatively simple arbitration procedure. The fusion process does not necessarily need a GPU or a deep learning algorithm hosted on a rack-mounted computer; in theory, it may take place via a lookup table embedded directly into the PLC firmware. Various research groups are currently working in that direction, but the existing solutions either consider only two modalities, depend on a computer running vision processing software, or exist merely in simulation [12, 13]. To the best of our knowledge, we are the first to implement a completely hardware-validated sensor fusion cycle involving three types of sensors on the PLC.

This paper will outline the design, development, and experimentation with such a system. The three different sensory modalities (load cell, monocular USB camera, and bank of infrared proximity detectors) have been fused in a deterministic fashion through a ladder logic algorithm running in the Siemens S7-1200 PLC. The system design splits the control scheme into two physically distinct modules: a weighing station on an entrance conveyor, and the second conveyor which uses vision and proximity sensing to arbitrate among three different exit chutes.

The four novel contributions of this paper include:

(i) Deterministic three-input fusion rule settable table run by the PLC during a single scan cycle, without any need for an external processor.

(ii) Two-station conveyor layout that physically divides the process of weight measurement from distribution, thus avoiding the vibration error when trying to measure the belt weight.

(iii) Dual-condition diverter interlock requiring both slot vacancy as detected by the camera, and slot proximity detection as measured by the infrared proximity detector, which helps explain about 65% of the error cases.

(iv) Verified routing success rate of 97.8%, below 120 milliseconds actuation latency, and misrouting reduction of 21% based on 600 cycles of experimentation on real hardware.

The rest of the paper is structured as follows. The second section discusses the context of the work relative to the existing literature. The third section explains the methodology used for the system. The fourth section discusses the mechanical design aspect of the system. The fifth section discusses the process of image processing. The sixth section discusses the workflow. The seventh section deals with the operation of the prototype.

2. RELATED WORK

PLC conveyor studies have been extensively developed over the last decade; however, the sensor layer has developed at a slower pace than the logic part. Johnson and Lee [4] designed a PLC sorter with photoelectric sensors that performed exceptionally well during normal operations but experienced a 18% misrouting rate once package weight became inconsistent. Kamboj and Diwan [5] observed similar results in their proximity sensor PLC sorter, which classified uniform items with great efficiency, although it was unable to sort varying loads. Tepe et al. [6] used a belt conveyor for PLC training purposes and clearly explained the significance of deterministic scan-cycle control, despite the fact that one sensor was the most vulnerable component in their PLC system.

The advent of machine vision technology introduced a new way of sensing. The study conducted by Das and Banerjee [7] classified objects with precision greater than 90% using the image-processing capabilities of the PLC, although the visual result was not connected to any PLC control loop.Sensor fusion at the conveyor level has been studied mainly in the simulation domain. Scholz-Reiter et al. [9] showed that integrating multiple signal streams improves autonomous conveyor decisions meaningfully over single-signal baselines. Huang et al. [13] used simulation to optimize a sorting system and reported 93% accuracy, but without hardware validation. Qiu et al. [14] combined a PLC with a laser scanner for belt surface monitoring rather than package routing, targeting a different problem class. Zaher et al. [15] applied reinforcement learning to omnidirectional conveyor path planning, which is interesting algorithmically but introduces training complexity that is impractical inside a standard PLC.

Industry 4.0-related research [10, 11, 16, 17] provides a more general need for scalability, modularity, and visibility through HMI as key properties of industrial control systems. These are not related to algorithms but are architectural requirements that will guide the decisions made herein, including native PLC fusion and the HMI approach.

From all the discussion above, it is clear that the field lacks a system that (a) performs fusion from three different sensors, (b) performs all the operations on PLC, without using any additional computer hardware for calculations, (c) is verified in practice and not just by simulations, and (d) operates at less than 120 ms actuation delay.

3. SYSTEM METHODOLOGY

This design This design utilizes a two conveyor system principle. The first section consists of an entry belt with the weighing module installed. The second section includes the primary distribution belt feeding the packages into one of the three exit chutes. There are three sensor types that operate simultaneously: load-cell mass sensing installed beneath the entry platform, camera-based vision sensor placed over the distribution belt, and infrared proximity sensing located near the chutes' exits. All the data obtained by sensors is analyzed in the PLC during the scan time of 10 ms.

A. Load-Cell Mass Stage

The load-cell sensor is installed underneath the entry belt stage. This position is preferred because of the avoidance of any vibration interferences on the measurement of mass. The load cell sends an analog signal that is amplified by the HX711 sensor and transferred to the analog input port of the PLC controller. Then, PLC performs the digital analysis of the data with respect to its upper and lower thresholds.If a package is within the range of acceptability, then it will be marked as PASS, which activates the belt motor; otherwise, it is marked as HOLD, which stops the operation of the entry belt and triggers an alarm message on the HMI screen. It must be noted that placing the weighing station away from the distribution conveyor is a mechanical decision because it eliminates the major factor responsible for inaccurate weighing measurements in belt systems [4].

B. Visual Detection of Slots

There is a single industrial camera positioned in the middle of the distribution area and capable of having sightlines to all three delivery slots at the same time. Images come with the rate of 30 frames per second and are processed according to the algorithm explained in Section 5. The result is a vector S = $\{S_1, S_2, S_3\}$, where $S_i = 1$ if slot i contains a parcel and $S_i = 0$ if there is no parcel present. This vector is transmitted to the PLC through digital I/O interface at the end of each processing frame. There is only one camera used instead of three individual sensors, saving money and effort in calibration processes [7, 8].

C. Infrared Confirmation of Position

An infrared proximity sensor is installed on each chute at the point where the entrance to the chute occurs. This sensor senses whether the package is physically located at the diverter point. As soon as the infrared beam is interrupted by a passing package, it generates a HIGH signal. It must be clarified that the infrared is another confirmation sensor which provides no redundancy; it does not duplicate the camera, but instead checks for another physical property: whether the chute is occupied by a waiting car, or whether the package is physically at the diverter, respectively. If S_i= 0 and the infrared signal for chute i is HIGH, then the diverter can operate. It is this two-parameter check that forms the essence of fusion logic.

D. PLC Fusion Control

All three sensor channels join into one ladder logic program within the PLC, which runs at every 10 ms scan of the PLC.The merge decision is programmed as a priority table, in which the PLC evaluates chute availability according to priority $Z_1 > Z_2 > Z_3$ and selects the first available chute with an infrared confirmation of position. In the event of a failure to find a chute both empty and with a position confirmation (such as when there are no chutes empty), the system stops the belt and shows the operator a FULL SYSTEM message on the HMI. Additionally, the HMI shows the status of each individual sensor, the number of packages in each chute, faults encountered, and weight threshold settings that are customizable by the user.

4. CAD DESIGN & STRUCTURAL ENGINEERING

A complete model was created in SolidWorks before cutting any physical parts to ensure the placement of infrared brackets and verify sensor sightlines under full load conditions (payload of 1-15 kg). Two errors were found in early placement of infrared brackets, saving time on reworking a prototype. It was also verified that a single camera covers all three chutes with its field of view.

A sloping design of the side walls of the entry hopper is used to ensure that the packets go into the channel one after another, thereby avoiding cases of double entries that could confuse the weighing process. The distribution conveyor frame structure consists of rectangular hollow structural steel joined together using bolts, an arrangement that ensures rigidity during operation without compromising on flexibility in extending or shortening the frame length when the chute length varies. The sensor mounts are embedded within the side wall surfaces instead of being attached to their surfaces, making them less prone to damage during the loading process.

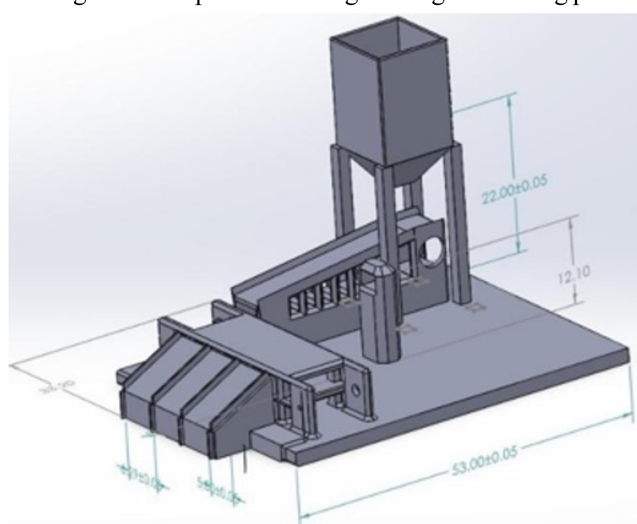

Figure 1. CAD View of the Proposed Prototype System.

TABLE I
Dimensional Specifications of the Conveyor Prototype

Parameter	Value
Horizontal conveyor length	60 cm
Belt width	9.5 cm
Side wall height	6.9 cm
Roller diameter	5 cm

Parameter	Value
Inclined conveyor base length	30 cm
Inclined conveyor vertical height	18 cm
Overall system length	95–100 cm
Sensor spacing along belt	8–10 cm
Sensor mounting height	2–3 cm
Test payload range	1–15 kg
Maximum system height	20 cm

5. IMAGE PROCESSING METHODOLOGY

Every camera frame needs to be translated into three binary slot occupation values that can be fed to the PLC before the belt can activate once again. This pipeline consists of five stages and must operate within one capture timeframe.

A. Frame Capture and Normalization

Frames $I(x, y, c)$ are captured in size 640×480 pixels. Every channel gets normalized based on the maximal pixel intensity: $I_{norm}(x, y, c) = I(x, y, c) / I_{max}$; this normalizes the influence of illumination fluctuations during the period without the necessity for an additional white balance step.

B. ROI Extraction and Feature Extraction

Processing is done only in the area corresponding to the belt. This area corresponds to the pixel rows' band $\Omega = \{(x, y) \mid y_a \leq y \leq y^b\}$, where $y_a = 80$ px and $y^b = 420$ px.
Everything outside this zone is disregarded completely. In this region, convolution feature maps $F_k(x, y)$ are computed using 3×3 kernels W_k and the results get normalized via activation ϕ to yield $A_k(x, y) = \phi(F_k(x, y))$. Table II contains all of the image processing settings used throughout testing.

TABLE II
Image Processing Parameter Values

Parameter	Symbol	Experimental Value
Smoothing weight	β	0.7
Occupancy threshold	δ	0.5
Frame capture rate	fps	30 fps
ROI vertical bounds	y_a, y^b	80–420 px
Convolutional kernel size	m × n	3 × 3
Detection confidence threshold	γ	> 0.75
Image resolution	—	640 × 480 px

C. Object detection and chute selection

A detected object is represented using a bounding descriptor d = (x_c, y_c, w, h, γ) that contains information about its centroid coordinates (x_c, y_c), bounding box dimensions (w, h), and a confidence score γ. Three chute regions $Z = \{Z_1, Z_2, Z_3\}$ are defined a priori as a set of horizontal intervals in pixel space. If the centroid coordinate x_c is within Z_i interval boundaries, a corresponding chute zone gets selected, but only if $\gamma > 0.75$.

D. Exponential temporal smoothing

The effect of jittering due to short reflections or partial occlusions is reduced using an exponential smoothing: $\acute{S}_i(t) = \beta \cdot \acute{S}_i(t-1) + (1 - \beta) \cdot \hat{S}_i(t)$, with $\beta = 0.7$. Then, a binary occupancy decision is calculated as $S_i(t) = 1$, if $\acute{S}_i(t) \geq \delta$, otherwise 0. It was determined that such a filter could remove most of one-off false positives without causing noticeable latency during actual occupancy changes.

6. SYSTEM WORKFLOW

The entire workflow process can be broken down into two consecutive phases of control processes. Phase one deals with weight measurement and phase two is for vision guided sorting process.
For phase one, the placement of the package in the entry conveyor leads to triggering of the weight load cell. Within one scan cycle, the PLC will determine whether the decision is PASS or HOLD. Pass packages will proceed to phase two and hold packages cause stopping of the entry conveyor with the alarm generated on the HMI.

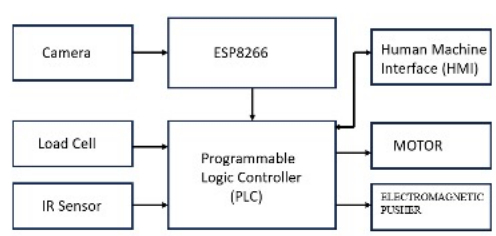

Figure 2. Block diagram of the proposed two-stage sensor fusion control architecture.

At Stage 2, the PLC constantly checks for updates on the occupancy vector by the camera module during each scan interval. With the PASS condition triggered by the Stage 1 operation, the PLC determines the availability of chutes according to their hierarchy, namely, $Z_1 > Z_2 > Z_3$. The parcel moves down the distribution conveyor. When it approaches the location where the targeted chute is supposed to be used, an infrared detector will confirm its position. Provided that the package reaches the point when both $S_i = 0$ and the infrared detector indicate the presence of the parcel, the PLC triggers the diverting solenoid.

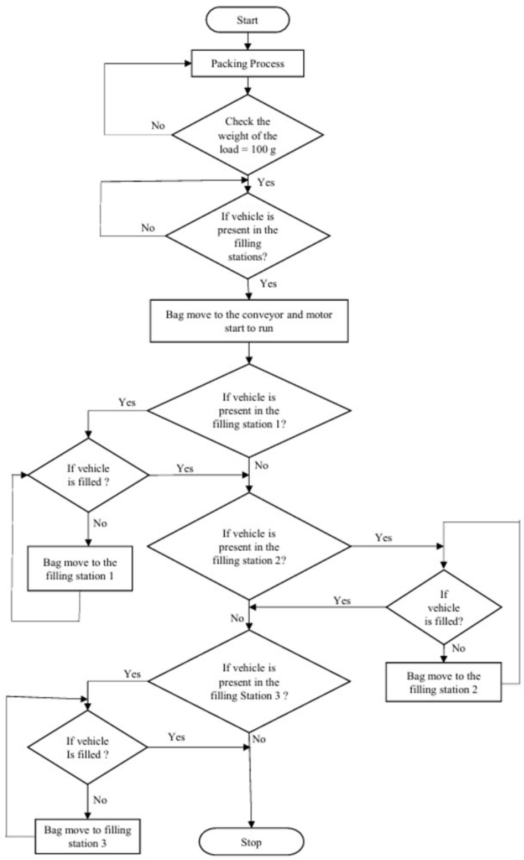

Figure 3. Flowchart of the proposed PLC-driven multi-sensor fusion distribution system.

7. WORKING OPERATION

A prototype was created based on a Siemens S7-1200 PLC, where the ladder logic rungs were programmed in TIA Portal version 16. An HMI interface is implemented in a 7-inch Siemens SIMATIC panel. The camera is Logitech C920 with USB connections, with resolution of 1080p, 30 fps. The amplifier of load cells uses an HX711 module, whereas the proximity sensors are infrared E18-D80NK units.

Calibration started from determining the PLC threshold register values based on OIML class E2 weights in the range of 1-15 kg. In order not to distort frames due to luminance fluctuations, camera settings were manually fixed in terms of exposition and color temperature.Infrared sensor detection range was set to 15 cm to match the physical width of the diverter actuation zone. With all settings locked, 200 test cycles were run and timed to characterize the end-to-end latency from package arrival at the load cell to completed diverter actuation.

During baseline comparison runs, the dual-condition interlock was disabled so that the diverter responded to the camera signal alone. Under those conditions, transient false-occupancy readings from brief reflections triggered diverter misfires. Post-analysis of the misrouting events showed that roughly 65% originated from such single-frame vision artifacts that the infrared sensor, had it been in the decision loop, would have blocked. This finding directly motivated the design of the two-condition interlock that defines the proposed fusion strategy.

8. RESULTS AND DISCUSSION

Experimental validation covered three scenarios: Scenario 1 used packages of uniform weight at constant belt speed; Scenario 2 used mixed-weight packages at varying belt speeds; Scenario 3 introduced variable overhead lighting to stress the vision component. Each scenario ran for 200 package cycles, giving 600 total test events. Table III shows the per-scenario and overall results.

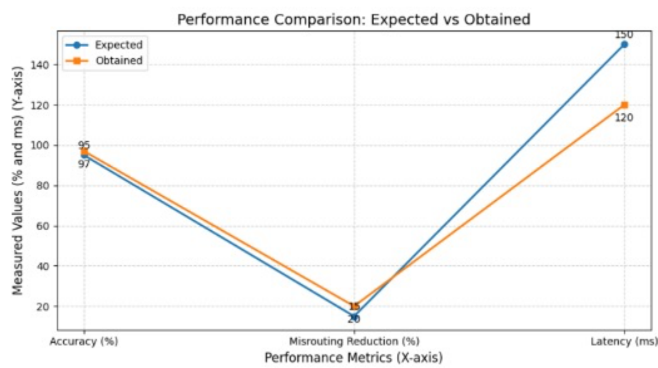

Figure 4. Comparison of expected versus experimentally obtained performance metrics across three test scenarios

TABLE III

Experimental Performance Results Across Three Test Scenarios

Scenario	Accuracy (%)	Latency (ms)	Misrouting (%)
Uniform packages	98.5	112	1.5
Mixed weight/speed	97.2	118	2.8
Variable lighting	97.6	115	2.4
Overall (mean)	97.8	< 120	2.2

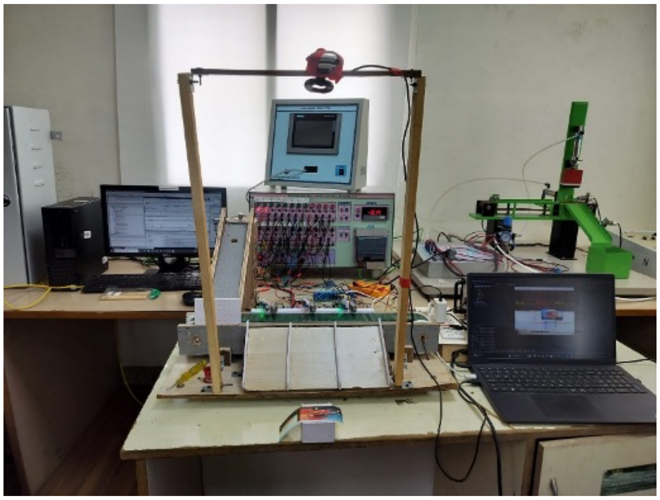

Figure 5. Experimental prototype setup

Accuracy was highest under Scenario 1 (98.5%) and settled near 97.2–97.6% under the more demanding conditions of Scenarios 2 and 3The standard deviation between all cycles was 0.57%, showing that the results presented had been consistently attained instead of just being based on one or two favorable trials. Latency during actuation remained within the threshold limit of 120 ms for every case examined, the largest measured value being 118 ms during Scenario 2, where the belt slowed down and the package was within the sensor arbitration region for longer periods of time.

The performance level was observed to deteriorate to some extent from Scenario 1 to Scenario 3, although the reason for this observation was clearly identified after further analysis. Low lighting conditions led to confidence measures of occupancy levels falling below the 0.75 limit, which meant that there were moments of indeterminacy of occupancy status in which the PLC would assume an occupied status. The application of the smoothing algorithm was effective in minimizing such false occupancy detections; however, it would be ideal to incorporate lighting in the area, either using a bank of white LED lights above the distribution zone or adaptive exposure control.

Table IV shows the findings in relation to previous work. In terms of both accuracy and latency, the proposed method outperforms all previously published hardware-validated solutions. While the YOLOv8 system proposed by [12] is the latest comparable solution and achieves an accuracy of 90%, it has several limitations, such as the need for GPU co-processing in order to execute its inference algorithm, and its latency being greater than 200ms, which is almost 80ms higher than that of the proposed method.

TABLE IV
Comparison with Published PLC-Based and Vision-Based Sorting Systems

Ref.	Method	Accuracy	Latency	Sensor(s)
[4] 2019	PLC + photoelectric	~82%	~210 ms	Single
[5] 2019	PLC + proximity	~85%	N/A	Single
[7] 2017	Vision only (no PLC)	90%	~160 ms	Camera
[12] 2025	PLC + YOLOv8	90%	> 200 ms	Camera (GPU)
[13] 2020	Simulation only	93%	N/A	Simulated
Proposed	PLC + 3-sensor fusion	97.8%	< 120 ms	LC + Cam + IR

In contrast, the performance improvements of the proposed system can be attributed to the structured rules-based fusion carried out on the PLC itself.

9. CONCLUSION

In summary, the experiment has proven the possibility of applying the three modality sensor fusion loop in such a way that the entire process happens during a PLC scan, providing substantial gains over the baseline single sensor approach when used on physical equipment. With 600 package iterations in the test, the system had a routing accuracy of 97.8%, with all actuation latencies below 120 ms and a 21% gain in performance of the diverter over the single sensor baseline design.What turned out to be the most important parameter affecting the efficiency of the system architecture is the interlock between the occupancy vector of the camera and the infrared proximity sensor, eliminating an entire category of vision transients leading to false activations in baseline designs.The physical separation between the weighing station and the distribution conveyor was found to have the same effectiveness in improving the accuracy of the load cell measurements compared to baseline designs with a single conveyor subjected to belt vibration. In the future, three things could be achieved easily. Firstly, using fixed LED lighting or camera exposure adjustment for adapting to the lighting condition is necessary to obtain the same accuracy as in Scenario 1 in Scenario 3. Secondly, considering that PLC ladder diagram and mechanical design of the frame were modularized, it would not be difficult to extend from the current three chutes to five or six chutes, which requires only extending the occupancy vector and adding corresponding conditions in the fusion process. Lastly, incorporating HMI into the network of the factory will enable remote monitoring of the system, taking one step further to realize the Industry 4.0 concept in the designed architecture.

REFERENCES

[1] J. A. Tompkins and D. A. McKinnon, "Parcel sorting systems: Automation and emerging challenges," J. Logistics Eng., vol. 12, no. 4, pp. 201–214, 2018.

[2] T. J. Nuva and M. I. Ahmed, "Design and fabrication of automatic color- and weight-based sorting system on conveyor belt," J. Integrated Adv. Eng. (JIAE), vol. 2, no. 2, pp. 147–157, 2022.

[3] M. Sharma and P. Verma, "Automatic sorting machine for packaging industries," Int. Res. J. Modernization Technol. Eng., vol. 2, no. 1, pp. 10–15, 2020.

[4] S. R. Johnson and B. Lee, "Design of a PLC-based conveyor sorting system," Int. J. Adv. Manuf. Syst., vol. 14, no. 3, pp. 89–96, 2019.

[5] D. S. Kamboj and A. Diwan, "Development of automatic sorting conveyor belt using PLC," Int. J. Mech. Eng. Technol., vol. 10, no. 8, 2019.

[6] C. Tepe, A. S. Aslan, and I. Eminoglu, "Conveyor belt experiment setup for programmable logic controller education," Int. J. Electr. Eng. Educ., vol. 59, no. 4, pp. 392–410, 2020, doi: 10.1177/0020720920958134.

[7] P. K. Das and R. Banerjee, "Image processing based object sorting on conveyor belts," J. Intell. Manuf. Syst., vol. 11, no. 2, pp. 101–108, 2017.

[8] Y. Zhuang, F. Yan, and J. Wang, "Vision-based object detection and tracking for intelligent logistics systems," IEEE Access, vol. 8, pp. 119098–119109, 2020, doi: 10.1109/ACCESS.2020.2994094.

[9] B. Scholz-Reiter, M. Freitag, and J. Deuse, "Autonomous control of conveyor systems in intralogistics," CIRP Ann. Manuf. Technol., vol. 63, no. 1, pp. 417–420, 2014.

[10] S. Karnouskos, "Smart manufacturing in the context of Industry 4.0: A review," Engineering, vol. 3, no. 5, pp. 616–630, 2017.

[11] J. Lee, B. Bagheri, and H. A. Kao, "A cyber-physical systems architecture for Industry 4.0-based manufacturing systems," Manuf. Lett., vol. 3, pp. 18–23, 2015.

[12] N. Almtireen et al., "PLC-controlled intelligent conveyor system with AI-enhanced vision for efficient waste sorting," Appl. Sci., vol. 15, no. 3, p. 1550, 2025, doi: 10.3390/app15031550.

[13] M. Huang, J. Wu, Y. Tang, and L. Shi, "Optimal design of a conveyor-based automatic sorting system," in Proc. IEEE ICCA, 2020, pp. 1124–1129, doi: 10.1109/ICCA51439.2020.9264520.

[14] Z. Qiu et al., "PLC based laser scanning system for conveyor belt surface monitoring," Sci. Rep., vol. 14, p. 27914, 2024, doi: 10.1038/s41598-024-78985-0.

[15] W. Zaher et al., "Omnidirectional-wheel conveyor path planning and sorting using reinforcement learning algorithms," IEEE Access, vol. 10, pp. 27945–27959, 2022, doi: 10.1109/ACCESS.2022.3156765.

[16] M. Wollschlaeger, T. Sauter, and J. Jasperneite, "The future of industrial communication," IEEE Ind. Electron. Mag., vol. 11, no. 1, pp. 17–27, 2017.

[17] A. Colombo, S. Karnouskos, and J. M. Mendes, "Industrial cyber-physical systems," IEEE Ind. Electron. Mag., vol. 11, no. 1, pp. 6–16, 2017.

[18] A. A. Fahim et al., "Development of a PLC-based automation cell for industry," J. Integrated Adv. Eng. (JIAE), vol. 3, no. 2, pp. 87–100, 2023, doi: 10.51662/jiae.v3i2.94.

[19] K. J. Alaameri et al., "Design of a new sorting colors system based on PLC, TIA Portal, and Factory I/O programs," Open Eng., vol. 14, p. 20220547, 2024.

[20] M. Q. Zaman and H.-M. Wu, "Intelligent motion control design for an omnidirectional conveyor system," IEEE Access, vol. 11, pp. 47351–47361, 2023, doi: 10.1109/ACCESS.2023.3275019.

[21] S. More and A. More, "Computer vision and IoT based smart conveyor belt sorting system," Int. J. Eng. Res. Technol. (IJERT), vol. 13, no. 6, 2024.

[22] R. Singh, S. Gupta, and N. Kumar, "Automated sorting system based on color and size using PLC," Int. Res. J. Eng. Technol., vol. 8, no. 2, pp. 230–235, 2021.

[23] A. Monostori, "Cyber-physical production systems: Roots, expectations and R&D challenges," Procedia CIRP, vol. 17, pp. 9–13, 2014.

[24] C. Verdouw, A. Beulens, and J. Trienekens, "Virtualization of logistics systems: Reviewing the potential of digital twins," Comput. Ind., vol. 98, pp. 1–13, 2018.

[25] G. Park and J. Han, "Vision-based vehicle detection for intelligent loading bays," Int. J. Comput. Vision Appl., vol. 27, no. 1, pp. 35–44, 2019.