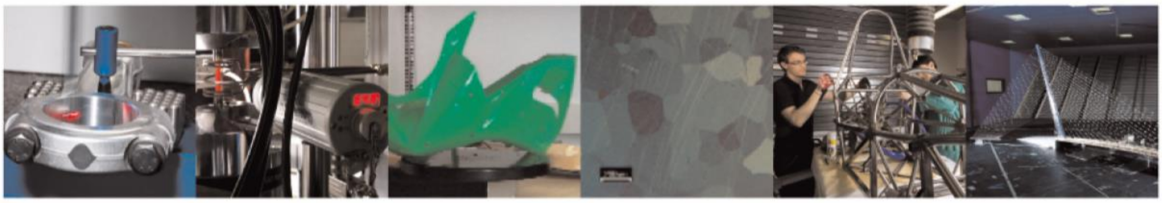

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Function-based Selective and Adaptive Cyber-Physical Assembly System for Increased Quality in Optoelectronics Industry

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Abstract

Recent advances in smart manufacturing technologies combined with the growing emphasis on zero-defect manufacturing paradigm set a premium on defect mitigation strategies in low-volume production systems. Assemblies for high-tech, high-variety products are becoming more complex, necessitating the need for in-line inspection, prediction, and prevention mechanisms; since the state-of-art end-of-line quality gates are error-prone due to accumulation of variability and errors from heterogenous sources, originating in upstream process stages. This paper proposes a dynamic function-oriented selective and adaptive assembly based on Cyber-Physical System (CPS) capabilities in order to meet changing product quality standards while enhancing the flexibility of the underlying strategy. A real-case study in optoelectronics industry is used to test and validate the method, highlighting the major benefits of the suggested methodology in terms of final product quality.

Keywords: Assembly, Optimization, Cyber-Physical System, Zero-Defect Manufacturing

1. Introduction

The rising use of customer-tailored, cutting-edge assemblies in high-added value sectors such as automotive, electronics and healthcare brings the challenge of continuous on-time delivery with preserved quality and sustainability. The delays in supply chain, especially in post-pandemic scenario, postpone the delivery of critical raw-/semi-finished materials, which undermines the due-date performance, reputation of the organization, and ultimately its ability to compete on the global market. Moreover, the eco-friendly approach through more efficient use of resources, while reducing the production costs generates a constant pressure on reduction of defects and non-conforming outputs. Although the traditional quality control techniques such as Lean Manufacturing, Six- Sigma and Total Quality Management (TQM) are proven to be useful so far, therefore widely adopted, in mass production environments to ensure the end-of-line product characteristics meet the specifications, they fall short to proactively compensate the production losses imposed by today's ever-fluctuating demand and massive customization requirements in small-lot down to individualized, one-of-a-kind production contexts, since the traditional methods rely solely on the historical data to identify certain patterns and trends meanwhile neglecting the present dynamics (Psarommatis, Sousa, Mendonça, & Kiritsis, 2022). Hence, manufacturing industry strives to utilize innovative, integrated and digital technologies provided by the fourth industrial revolution, Industry 4.0, for sustainable, agile, resilient systems that are capable of exploiting sophisticated Zero-Defect Manufacturing (ZDM) techniques that comprehensively take into account quality, production logistics, and maintenance aspects (Tolio & Colledani, 2014).

Zero-Defect Manufacturing (ZDM) is an emerging concept to exceed beyond the traditional quality control techniques. The philosophy behind ZDM is to eliminate defects by not only through *detection* and *correction* (e.g. repair, rework), but also through *prediction* and *prevention* mechanisms to achieve "first-time-right" (Powell, Magnanini, Colledani, & Myklebust, 2022) (Psarommatis F. , May, Dreyfus, & Kiritsis, 2020) (Psarommatis, Prouvost, May, & Kiritsis, 2020) (Powell, Eleftheriadis, & Myklebust, 2021). Therefore, the in-line gathered data from manufacturing system, equipped with sensor and monitoring networks, needs to be elaborated in real-time to evaluate current system state and predict a priori the possible evolution scenarios to enable promptly the preventive measures. For instance, since the processes without any intervention have a natural tendency to exceed their control limits due to various reasons, e.g. process instability, each processing stage introduces a deviation from nominal product feature. Thanks to the recent advancements regarding 100% in-line inspection technologies (Azamfirei, Psarommatis, & Lagrosen, 2023), early detection of these deviations allows to prevent the superimposition of unidentified or understudied effects which eventually result in high scrap rates. Furthermore, early detection facilitates the activation of corrective actions before the defective parts undergo irreversible transformations. However, according to the state-of-art, the inspection and testing stages to assess the product quality and functionality usually take place at the end-of-line, where different sources of variability and errors originated in upstream process stages are aggregated. Following the completion of all the processes on the product, it becomes significantly more challenging and expensive to repair and reuse the components. Hence, scrapping or rework remains as the only viable alternatives despite the low-added value. This phenomenon is more evident in assembled complex parts, as in the case of optoelectronics which is characterized by high-tech, high-complexity and high-customization products, where the disassembly requires non-negligible additional time. As a consequence, annihilating economic losses may be encountered due to scraps or lost time for defect correction.

The Key Quality Characteristics (KQCs) of a complex assembly are subjected to the interactions between the quality characteristics of composing sub-components. Therefore, the variability at the component level is propagated to the assembled product level in case of a functional deviation is observed from in-isolation to joint working conditions (Colledani & Demir, 2022). A commonly confronted situation in manufacturing industry is that the conforming components comply with tight tolerances and accepted in quality control gates, however they are subjected to critical deviations (e.g. consistent measurements near the specification/control limits, *SL/CL*); indicating potential downstream quality issues, in particular during the assembly. Selective assembly is suggested as systematic means of producing high precision assemblies from comparably lower precision pieces to cope with this issue. It is based on in-line inspection, component sorting into classes according to their quality, and ultimately finding the optimal matching units to be assembled. The traditional selective assembly applications consist of products with simple variability propagation patterns, for instance, mechanical components with static and linear matching functions (e.g. the gap between piston and cylinder or pin and bush). This prohibits the use of selective assembly for low-volume, customisation intense applications because it relies on large measurement data sets for fitting component KQCs statistical distributions. Besides, due to its strict and static matching and assembly procedures which increase the logistical complexity at the system-level and the creation of deadlock states, selective assembly has limited use in the industry. Figure 1 demonstrates the selective assembly strategy for two component types (x,y).

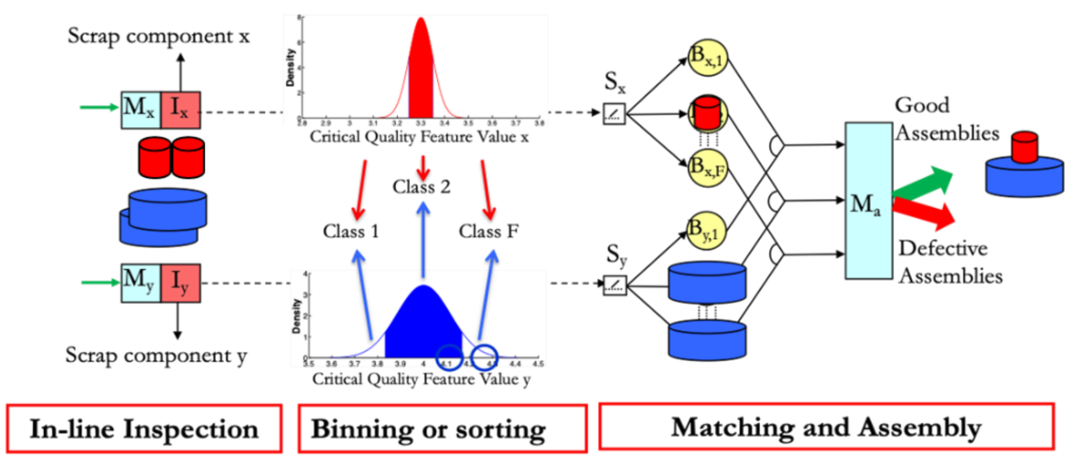


Figure 1. Selective Assembly *(Colledani, Ebrahimi, & Tolio, 2014)*

Nowadays, the industrial barriers for wider implementation of selective assembly is addressed by following rather a holistic approach targeting simultaneous realization of four core ZDM strategies: detection, correction, prediction and prevention. The in-line gathered time-series data about product, process or system is fused with the information about external factors (technological advancements, volume and customization demands from market, material availability in supply chain etc.) to develop and fine-tune the semantic algorithms at different hierarchical levels to comprehensively optimize manufacturing system performance, particularly for high-value parts, with lower complexity and higher efficiency. In that sense, collected information is exchanged horizontally within network of connected machines via Internet of Things (IoT) and vertically between multiple system layers through Manufacturing Execution System (MES). Based on the output of integrated digital solutions, preventive or corrective control actions are actuated system-wide in case of defect detection to achieve complete ZDM. In this context, Cyber-Physical Systems (CPS), the outcome of substantial developments in emerging information and communication technologies (ICT), are means to connect the cyber computational space and physical processes surrounded with sensors and monitors to control production systems (Monostori & Kádár, 2016).

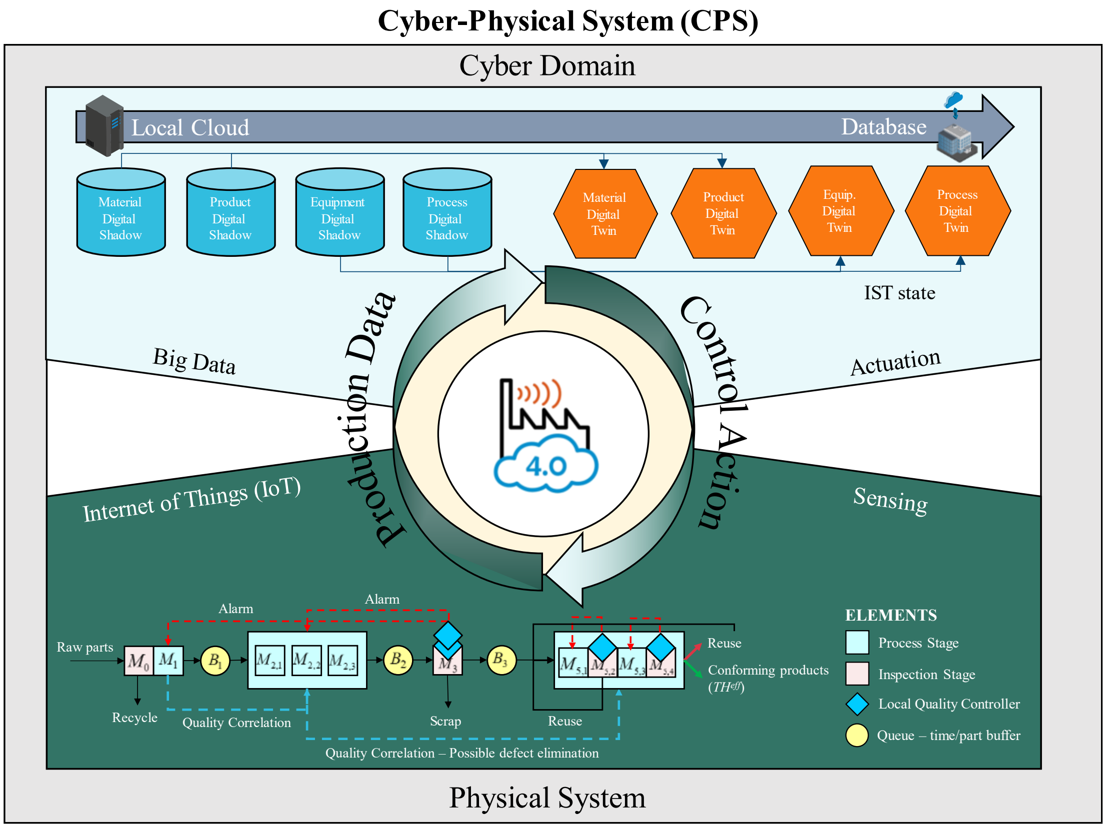


Figure 2. Cyber-Physical Production System (CPPS)

CPSs swiftly become quite useful in smart manufacturing due to their ability to integrate data analytics tools to elaborate massive amount of real-time gathered data, physics-based or data-driven models (e.g. digital twins, meta-models) to simulate stochastic behaviours and control loops to maintain process variables at a desired stable value. In ZDM framework, the increased use of sensors and in-line measurement instruments opens up the possibility for synchronous analysis of simulation models created during Research & Development (R&D) or design phase also during manufacturing, using empirical data obtained through systematic in-line observations as an input, for adjustment of machine settings for the next operation (Söderberg, Wärmefjord, Carlson, & Lindkvist, 2017). Thus, before the actual physical changeover, simulation results in the virtual domain can predict the outcome and support the decision-making of operator, or directly adapts process parameters. In addition to that, the lessons-learned at the end, which is often overlooked in traditional control methods, deepens the product and process know-how that mainly depends on operator expertise (e.g. qualified or non-qualified), and provides valuable feedback to establish causal relationships.

With the implementation of CPSs, Selective and Adaptive Production Systems (SAPS) that dynamically selects the individual elements in the queue to be assembled, taking into account their in-line measurements, are proposed. Although the SAPS have been beneficial so far in complex production environments, their application is bounded by the computational burden of the CPS. As a result, in various scenarios with large inventory and multi-dimensional component quality propagation patterns, rather than planar, the optimisation of selection procedure may lead to devastating computational times, interfering with assembly cycle-time, which turns the CPS into system bottleneck that must to be avoided. This article discusses a novel methodology to dynamically implement function-oriented selective assembly, rather than individual assembly that pairwise matches the components based on their feature characteristics; or geometry-based coupling in traditional selective assembly applications, based on CPS capabilities to satisfy everchanging customisation requirements for products with numerous variants. The proposed architecture primarily aims for defect *prevention* through the use of real-time data obtained from 100% in-line inspection, which separates ZDM from traditional quality improvement strategies. The benefits of component clustering are combined with optimisation algorithm, acting on selection to dynamically update the selection vector for evolving component matching function, to correctly balance the trade-off between quality and logistics performance of the assembly systems. Presented approach is tested and validated in a real case in optoelectronics industry in Prima Electro S.p.A. The results show that the final product quality with proposed system is remarkably improved compared to currently adopted First-in-First-Out (FIFO) strategy and discussed framework plays a key role to reach smart manufacturing and ZDM goals.

This paper is structured as follows: Section 2 presents the state-of-the-art, Section 3 describes the selective assembly system, Section 4 elaborates the proposed methodology, Section 5 demonstrates the real-case study from optoelectronics industry, Section 6 presents the achieved results, Section 7 is dedicated to discussions and Section 8 includes conclusions and future work directions.

2. Related Works and Contributions

Selective assembly has been researched in plenty of fields in the state-of-the-art. (Colledani, Ebrahimi, & Tolio, 2014) evaluated the system-level quality and production logistic performance of selective assembly in terms of two-level decomposition methodology, and shows that selective assembly increases the assembly yield, but it also contributes to the managerial complexity of the system by transforming the product quality problem into a system logistics problem due to the deadlock states caused by finite buffer capacity. (Tolio & Colledani, 2014) highlighted this subject through unveiling the interactions between production logistics, quality and maintenance. In the keynote, a new paradigm is proposed to replace traditional Six-Sigma techniques which show strong limitations in batch production, customised or one-of-a-kind products; moreover, the need for in-line, real-time monitoring at each process stage for quality control and process improvement is investigated. In (Kaufmann, Effenberger, & Huber, 2022), the authors make use of in-line integrated fringe projection system to build 3D point-cloud to be compared with nominal product CAD model and apply selective assembly to match injection-molded housings and covers for reducing scraps, focusing on detection and prevention aspects of ZDM. The virtual assembly to simulate physical assembly in this work belongs to broader category called Virtual Metrology (VM), a concept that reduces the physical measurements, therefore the inspection time and cost, by estimating the KQCs of a product with data-driven approaches (Dreyfus, Psarommatis, May, & Kiritsis, 2022). Taking the advantage of 100% in-line measurements, many attempts to apply selective assembly strategy to different sectors with strategic complex assemblies, such as e-mobility, have been made (Löchte, Kayasa, Herrmann, & Raatz, 2012) (Yang, Wang, Hu, & Lin, 2013) (Colledani, Coupek, Verl, Aichele, & Yemane, 2018). To that end, CPS-based SAPS have been proposed in (Kayasa & Herrmann, 2012) and (Lanza, Haefner, & Kraemer, 2015) used a holistic CPS-based matching to optimise SAPS performance. The experiments performed in real case study have considerably reduced the production costs and scrap rates. In this area, a viable and practical CPS architecture to increase product quality and system reliability is discussed in (Lee, Bagheri, & Kao, 2015) and (Lee, Jin, & Bagheri, 2017). However, the human-in-loop concept is barely emphasised in this architecture. More human-centric CPSs (HCPS) are presented in (Wang, Zheng, Yin, Shih, & Wang, 2022) and (Ansari, Khobreh, Seidenberg, & Sihn, 2018).

The ZDM solutions usually consist of a sophisticated production systems. A particular reference architecture to support digital manufacturing systems towards the multi-level implementation of ZDM strategies and to manage with distributed, multi-resolution and multi-scale data gathered from different sources is discussed in (Magnanini, Colledani, & D., 2020). But, such connected systems are surrounded by new embedded in-line sensor technologies that enable the continuous capturing of big bulks of data or so-called "Big Data" from the line, which brings the challenge of fusing heterogeneous data from multiple sources and the analysis of the data obtained (Lee, Davari, Singh, & Vibhor, 2018). As a matter of fact, the analysis results are used to select key performance indicators (KPIs) that show the necessary indicators to further investigate in data-driven decision-making tools for quality control (Eleftheriadis & Myklebust, 2019). In that sense, CPSs become the cornerstone to implement ZDM practices to the shop-floor in order to control production (e.g. maintenance scheduling, machine degradation, machine-level parameter control) (Martinez & Al-Hussein, 2022); on the other side, they provide feedback about the quality. In the event of defect detection, the feedback quality information activates defect management strategies in ZDM. In this regard, (Psarommatis & Kiritsis, 2022) presents a decision-support system to improve production performance through better defect mitigation and correction actions and (Schröder, Falk, & Schmitt, 2016) implements a failure classification and associated analyses for production ramp-up. Regarding the prediction kernel of ZDM, (Lee, Jin, & Bagheri, 2017) studied a maintenance system in ball-screw prognostics to reduce machine downtime through predictive analytics. Additional guidelines to ease the integration towards ZDM principles are given in (Psarommatis & May, 2023) and (Eleftheriadis & Myklebust, 2016), more in-detail on CPS in (Eger, et al., 2018) and (Chiariotti, 2018).

Even though these works are pertinent to manifest SAPS in ZDM context, a few number of researches take into account both the product quality and functionality. In (Wagner, Haefner, & Lanza, 2018), a simultaneous optimisation method of a function-oriented adaptive quality control strategy based on a product model is investigated. Since the optimisation of multi-stage control strategies require a significant effort, (Wagner R. , Haefner, Biehler, & Lanza, 2020) researched state-space model and a meta-model and (Aderiani, A. Wärmefjord, & Söderberg, 2020) proposes a novel one-to-one phenotype genotype mapping method to ease the computational load. Lastly, the function-oriented selective assembly in cross-industrial collaborative networks is investigated in (Silbernagel, Wagner, Albers, Trapp, & Lanza, 2021) and (Silbernagel, Wagner, Peukert, & Lanza, 2022).

3. System Description

The schema of the system in which functionality-oriented selective assembly is developed is shown in Figure 3. The concept can be extended for multiple component types and longer process chains in grounded on this.

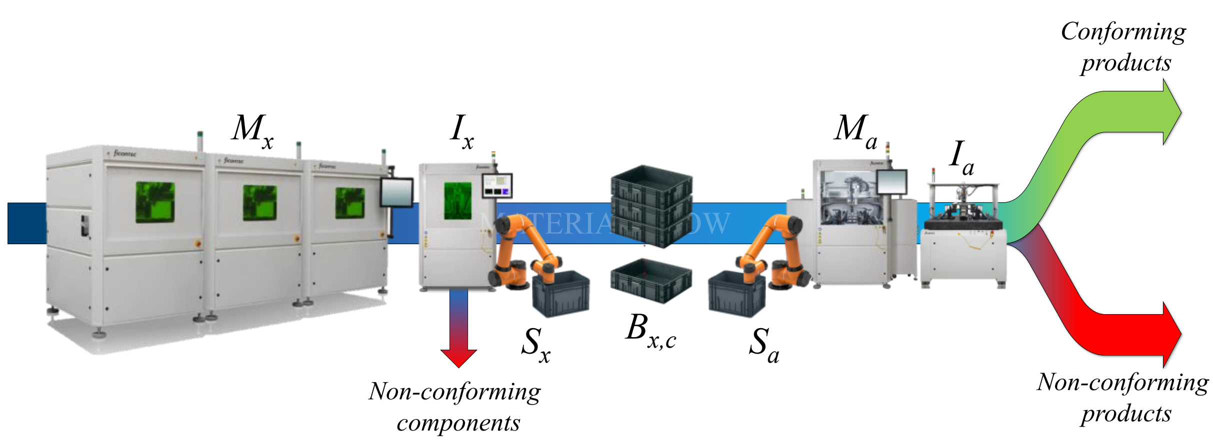


Figure 3. Representation of Selective Assembly System

The system is explained in the following. The sub-component of type x is processed by machine M_x, with processing rate μ_x. The sorter S_x implements a *Classification and Sorting policy* by clustering the components into buffers in accordance with in-line measurements of KQCs, which are in-line measured by inspection station I_x. A total number of C buffers store the x-type sub-components, namely $B_{x,c}$, with $c=1,\dots,C$. Components are then extracted by a selector S_a in accordance with an optimized *Assembly policy* and assembled by machine M_a with processing rate μ_a to obtain the final product. The assembly output is examined at machine I_a: the defective assemblies are scrapped, whereas the conforming assemblies are delivered as output.

The two key policies *Classification and Sorting* and *Assembly* is further elaborated in the following.

Classification and Sorting policy. Each buffer $B_{x,c}$ contains components with KQCs included between a lower limit $l_{x,c}$ and an upper limit $L_{x,c}$. The quality classes are contiguous, i.e. they respect the following properties: $L_{x,c}=l_{x,c+1}$, $\forall c=1,..,C-1$; $L_{x,C}=USL_x$; and $l_{x,1}=LSL_x$. USL_x and LSL_x represent the Lower and Upper Specification Limits of component x. I_x identifies a component as defective and discards it if its KQCs do not adhere to USL and LSL. Otherwise, it is sorted in class c and the level $N_{x,c}$ of buffer $B_{x,c}$ is updated, i.e $N_{x,c}(\tau)=N_{x,c}(\tau-1)+1$. At the same time, the mean KQC value of the parts stored in buffer $B_{x,c}$, i.e. $\overline{KQC}_{x,c}(\tau)$ is updated. Then, the subsequent CPS intelligent module receives these variables as input.

Assembly policy. The selector S_a extracts multiple parts at once from buffers and sends to be assembled in assembly machine M_a according to the optimal selection vector, α^{opt}, containing the number of components to select from each classes. Such vector is not fixed but repetitively defined as the final output of the CPS and the underlying optimization model. Differently from conventional selective assembly systems, the assembly policy considers only the ready-to-use components in the classes. Thus, deadlock states are avoided. Once parts are assembled, the buffer level $N_{x,c}(\tau+1)$ and the mean value of the KQC, $\overline{KQC}_{x,c}(\tau+1)$, in the related classes are updated.

4. Methodology

The proposed CPS-based methodology is given in-detail as follows.

4.1. CPS Architecture

The CPS workflow architecture illustrated in Figure 4 consists of a process chain, Manufacturing Execution System (MES) for operations management and control, and two intelligent modules: Classification and Assembling, for binning and optimal selection of components. The developed CPS incorporates the *'human-in-the-loop'* paradigm to guarantee traceability, extensive operator monitoring and learning, all of which are crucial for industrial enterprises. Through a dedicated User Interface (UI), i.e. Human-Machine Interface (HMI), the operator involves in and controls every stage of the process. The operator adjusts and approves the new settings in case production parameters or end-user requirements change. This enables to achieve the knowledge transfer systematically from digital technology to the users, providing a greater integration among the complicated manufacturing systems and humans.

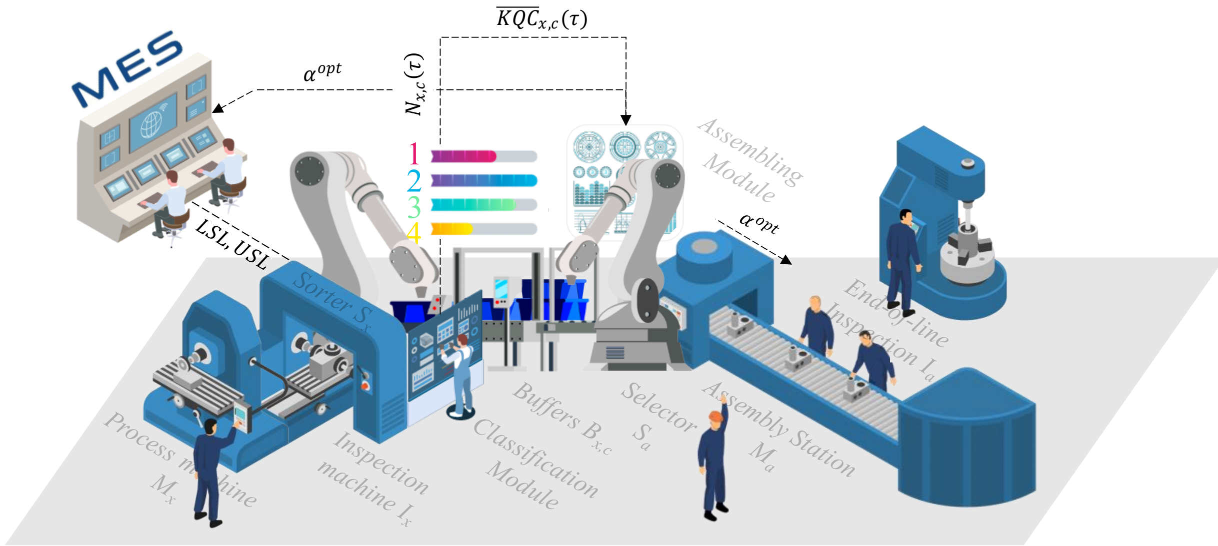


Figure 4. CPS Architecture

The in-line inspection allows the component KQC measurement acquisition directly from the manufacturing line. The first intelligent CPS module, *Classification Module*, actuates the sorter S_x to categorize the components into the corresponding quality classes, applying *Classification and Sorting policy*. The second module, *Assembling Module*, receives the classification results and refines them using data analytics tools and physics-based models to drive an optimisation algorithm, able to find the optimal blend of components to be assembled per product functionality requirements. The outcome of the Assembling Module is shared with MES and *Selector* to perform the assembling process. The 100% of assembled products pass through a final inspection process at end-of-line inspection machine I_a before leaving the system to be delivered to customers, in order to guarantee that no defective products are included in the shipment. The back-end of Assembling Module is explain in-detail as follows.

4.1.1. Assembling Module

The key building blocks of Assembling Module are explained in the following.

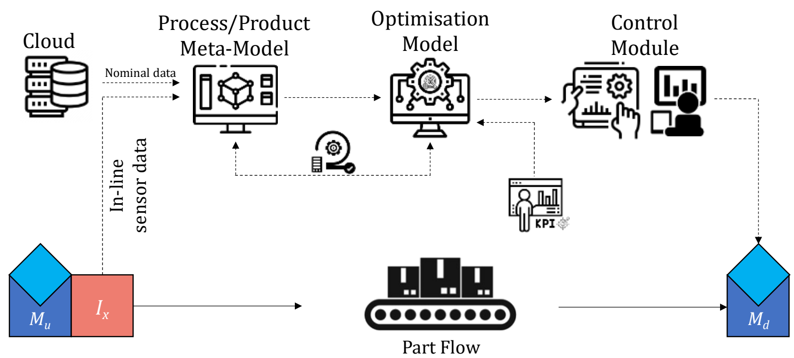


Figure 5. Assembling Module

Product meta-model, which incorporates data analytics and a physics-based model, links the component quality characteristics to the quality features of the assembled product. It elaborates the in-line gathered real-time data at stage M_x to anticipate a priori the output quality features and functional performance of the assembled component that will be processed at step M_a.

Based on iterative calls to the product meta-model kernel, ***Optimization Model*** dynamically searches the solution domain defined by the available components in buffers $N_{x,c}$ and their KQC mean value $\overline{KQC}_{x,c}$ to determine α^{opt}, which is then passed to the M_a. The objective is to minimise the gap between the target assembled component KQC value and its prediction provided by the product meta-model. The traceability of individual component measurements is compromised in favour of a dynamically updated, class-based statistics to decrease the required computational effort. Otherwise, depending on the problem's NP-hardness level the solver may take astronomical minutes to reach the global minimum.

Through the use of an HMI, ***Control Module*** shows the operator the optimal parameters to be used for the controlled process. Once the adapted parameters have been evaluated and verified by the operator, M_a receives the α^{opt}. Therefore, the CPS acts as an advanced feed-forward controller, reflecting the prevention principle of ZDM, to stop errors from propagating all the way to the end of the production line, protecting vital raw materials and lowering production costs and lead times in comparison to the scrapping scenario. Figure 6 depicts the simplified block diagram of a feed-forward controller CPS from a control system point of view. According to the measured anomaly in product or system state of upstream production processes, the parameters of the downstream production processes are controlled by a model-based approach in order to smooth variability and avoid an input defect to be transformed into an output non-conforming product. The procedure is applied through two main transfer functions, $C_p(z)$ and $C_f(z)$, acting both on the flow control level and on the process parameters.

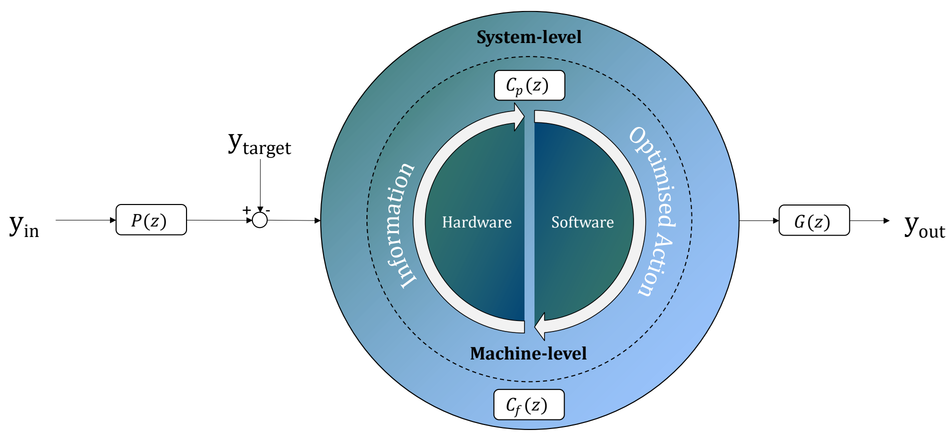


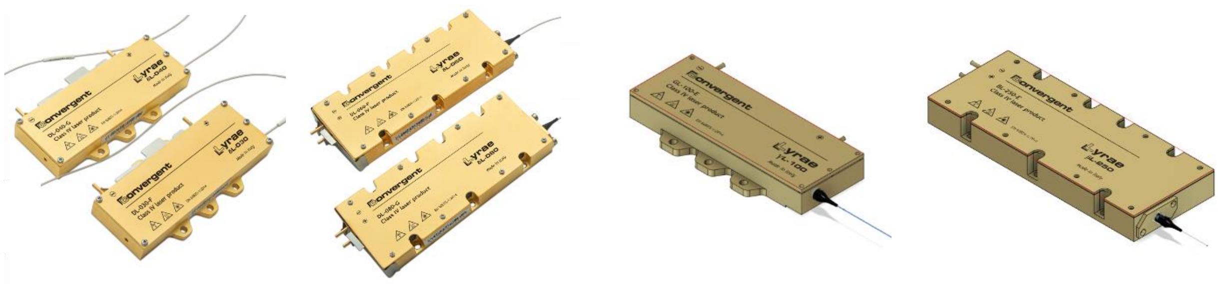
Figure 6. Feed-Forward Cyber-Physical System (CPS) Control

where y_{in} and y_{target} are the input and target signals respectively; $P(z)$ is the predictor; $C_f(z)$ is the flow and $C_p(z)$ is the parameters optimisation control modules; $G(z)$ is the controlled system; and y_{out} is the output signal.

5. Real-Case Study in Optoelectronics Industry

5.1. Industrial Context

Prima Electro S.p.A offers its own production line of high-power diode laser manufacturing and Fiber Laser Module (FLM) assembly, implementing strategies to increase the production efficiency and to reduce production costs through recycling and reconfiguration of products to maintain high quality standards of the outgoing product. Two multi-emitters are fabricated in Prima Electro premises: the BL-250-E at 976 nm. wavelength (250W) and the GL-100-E at 793 nm. wavelength (100W). In this study, multi-emitter laser sources at 976 nm. wavelength are used to be assembled into Multi-kW Yb-doped FLMs, typically used in material processing, to supply hundreds of watts of optical power at defined wavelengths. The assembled module must satisfy the challenging characteristics of emitted power, wall plug efficiency, laser beam quality and diode life under critical and variable operating conditions, with a complex dependency between the diodes and the resulting module characteristics.



a. BL-250-E **b.** GL-100-E

Figure 7. Multi-emitter Laser Sources

The laboratory in Turin, Italy consists of a front-end and a back-end of the diode laser products manufacturing with a flexible design, enabling a set of product families based on custom requirements and fluctuating market demand. The front-end is the manufacturing of single emitter laser source; whereas in the back-end, the Chip-on-Carrier (CoC) diode sources are soldered on a platform and electrically connected with Al wire bonding to obtain multi-emitter laser diodes. Figure 8 shows the primary three sections of Prima Electro's production line:

- ***Front-end,*** production of single-emitter laser diodes (red).
- ***Back-end,*** production of multi-emitter lasers with single emitter diodes as sources (blue).
- ***Fiber Laser Assembly,*** production of FLM (green).

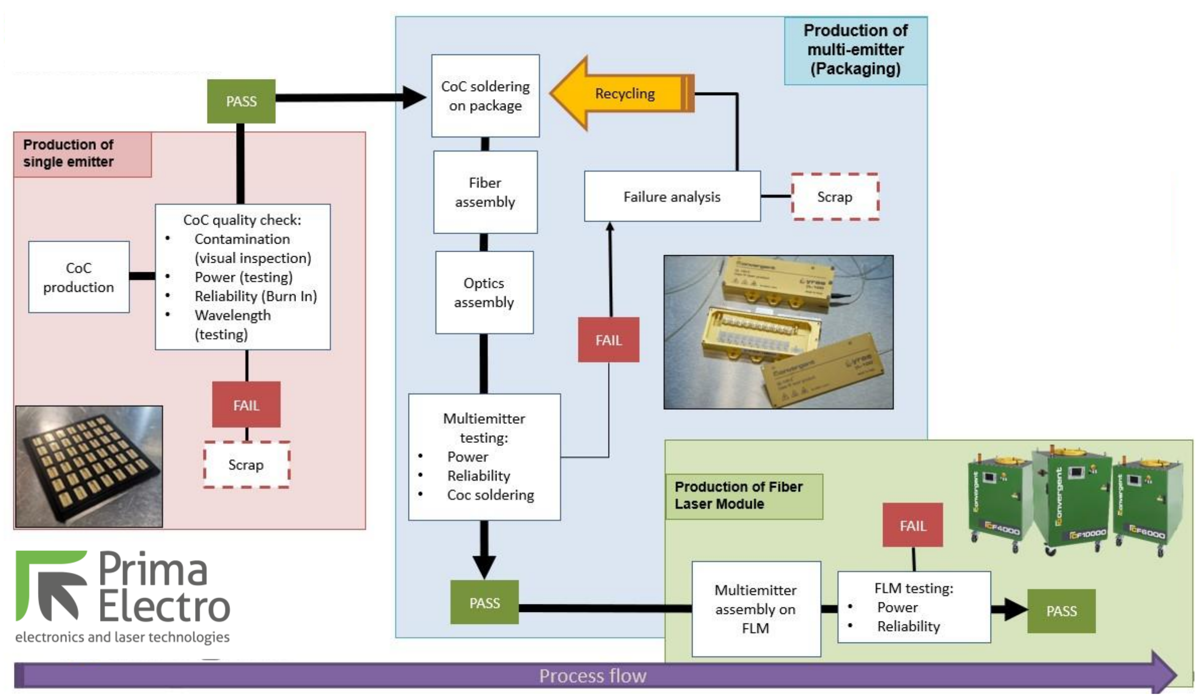


Figure 8. Production Line Schema in Prima Electro

The aim of Prima Electro is to overcome the challenges of improving the process monitoring and information tracking, handling the complex designs that include part functionalities, and controlling the performances through simulation tools for a new, flexible, and innovative process chain. During the manufacturing phase, by exploiting in–line inspection, data management platform and CPS architecture, the deviations and trends need to be analysed to react on the processes through innovative multi-stage system control solutions, moving towards ZDM implementations.

The proposed methodology has been implemented to improve the quality and system-level performance of the present assembly system, reducing the scrap rate of assembled modules, as is leading to material loss and cost increment.

5.2. Cyber-Physical System (CPS) Integration

The proposed CPS framework is customised for the implementation in Prima Electro, as explained in Figure 9.

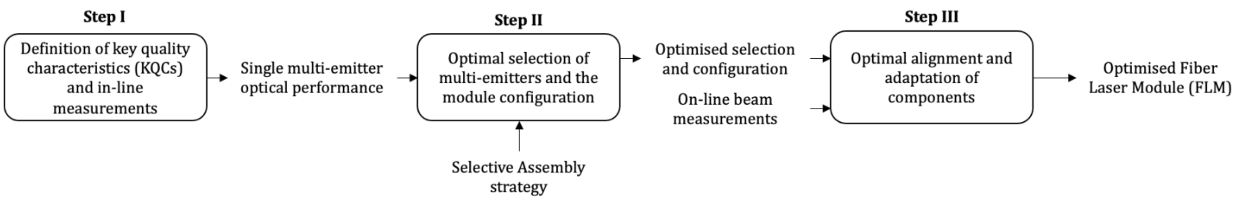


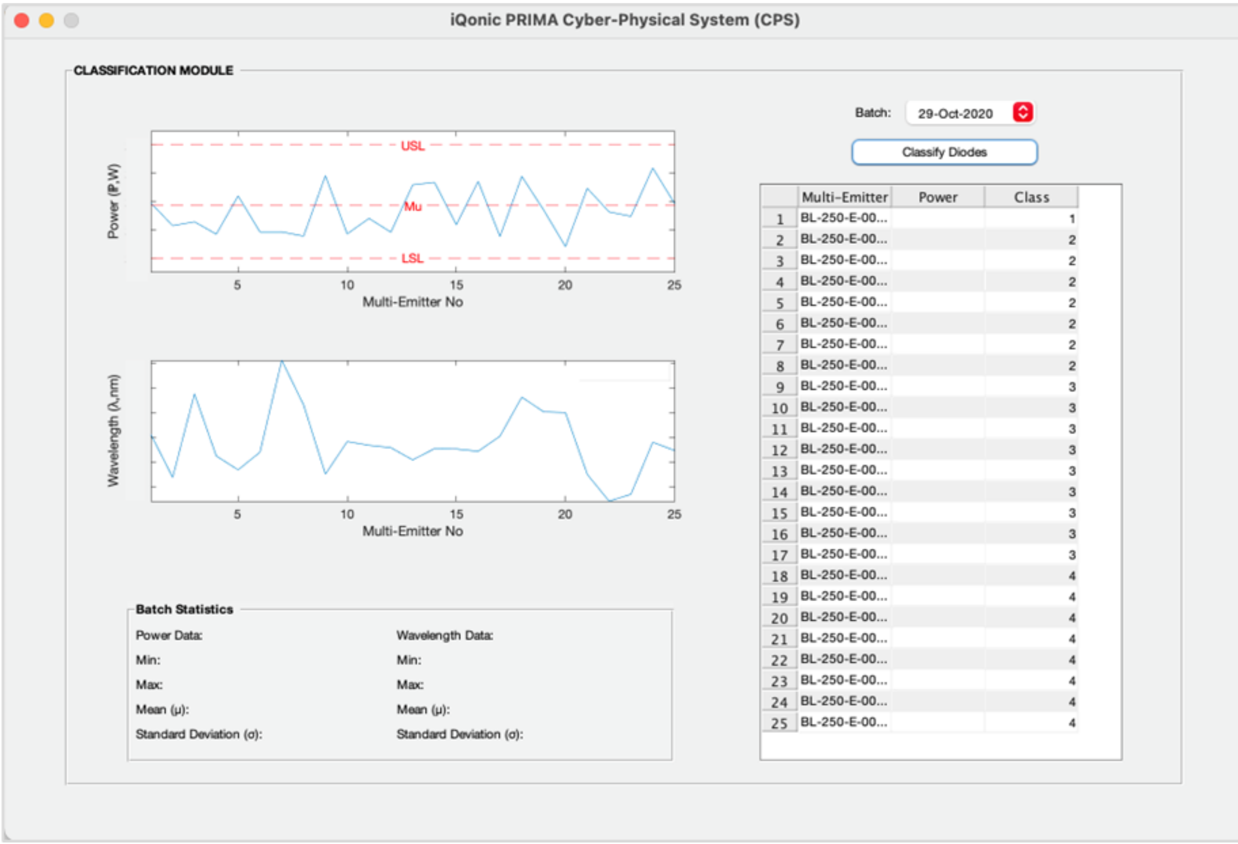
Figure 9. Cyber-Physical System Implementation Steps for Prima Electro S.p.A

KQCs of single multi-emitters regarding their optical characteristics are gathered from the production line in terms of power, beam quality and wavelength. These data are elaborated by the Classification Module to bin the components into quality classes. Then, the Assembling Module extracts the information from company MES about the customer-driven FLM specification and the component class-related data to decide the multi-emitter diodes to be selected for better FLM configuration featuring higher performance stability in terms of power uniformity, beam divergency and asymmetry. Thus, the optimised FLM is levelled by a CPS-based approach. Two key quality characteristics (KQC) of the diodes that affects the performance of FLM are the power *(KQC_1)* and the wavelength *(KQC_2)*. The power of single multi-emitters is directly correlated with the capability to generate the output power, while the wavelength affects the conversion efficiency (η) of FLM. The target power ($\mathbb{P}_{target}$) of the FLM is a user input defined by specifications. For instance, $\mathbb{P}_{target}$ is selected as 2.1kW in this study, which needs to be surpassed by the output power ($\mathbb{P}_{out}$). Since the working conditions influence the functionality of sub-components, it is at utmost importance to predict the behaviour of assembly output in advance to guarantee the final quality. Using physics-based models and the in-line measurements of inspected diodes, $\mathbb{P}_{out}$ can be predicted prior to assembly even though the exact value can only be determined once the FLM is fully assembled.

5.2.1. Intelligent Modules

To implement the proposed methodology, the two intelligent modules (Classification and Assembling) have been designed in MatLab environment.

Classification Module, sorts the processed components into quality classes. The user defines the design parameters *LSL* and *USL;* and based on the decided number of classes, the class interval and bounds are calculated. The in-line measured power and wavelength of single diodes are transferred to the Classification Module from the production line and the parts are binned into the buffers. At the end, the classification results are shared with the Sorter and Assembling Module.



**** Data are omitted due to confidentiality***

Figure 10. Classification Module Interface

Assembling Module, finds the optimal selection vector (α^{opt}), containing the information about selection of components from classes and their positioning in FLM, to be transferred to assembly stage. The transfer function connecting the diode KQCs and the FLM output KQCs is developed in this module.

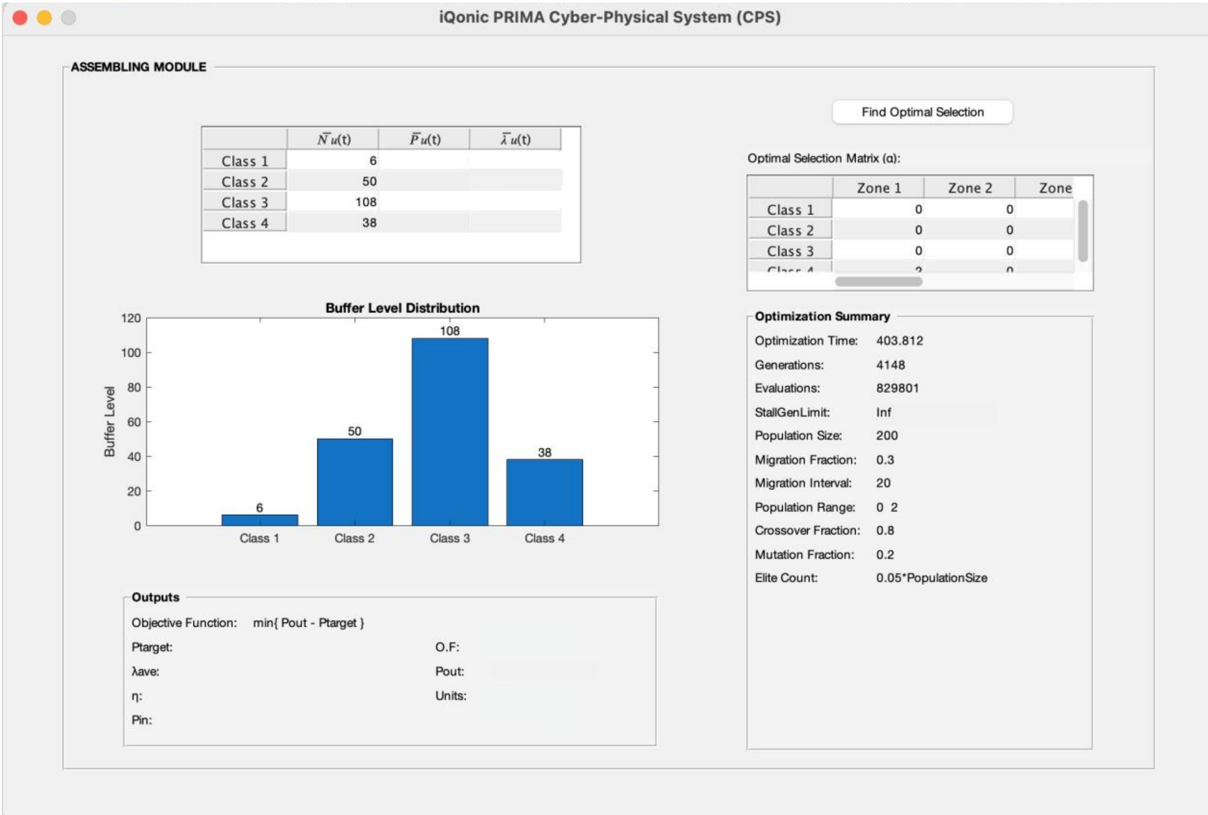


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Figure 11. Assembling Module Interface

The input power ($\mathbb{P}_{in}$) of FLM is equal to the sum of each composing diode power:

$$\mathbb{P}_{in}(\alpha) = \alpha^{opt} \times \overline{\mathbb{P}}_u(\tau) \tag{I}$$

λ_{ave} indicates the wavelength of FLM. It is equal to the average wavelength of optimally selected components.

$$\lambda_{ave}(\alpha) = \frac{\alpha^{opt} \times \bar{\lambda}^u(\tau)}{\sum \alpha^{opt}} \tag{II}$$

The wavelength of FLM influences the conversion efficiency (η) of the optical fiber laser which connects the output power to the input power. The data analytics results that correlates the efficiency and FLM wavelength is shown in Figure 12.

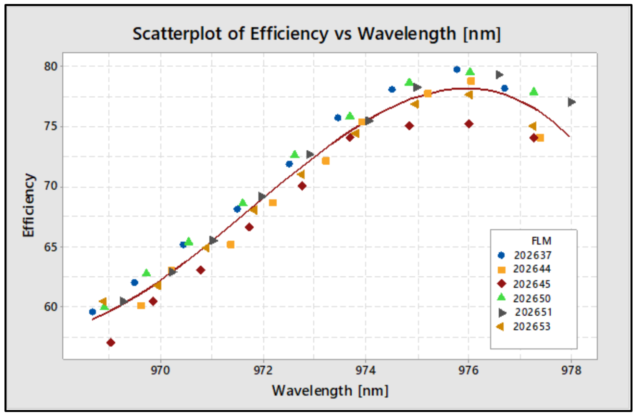


Figure 12. Efficiency ($\mathbb{P}_{out}/\mathbb{P}_{in}$) vs. Wavelength of FLM

Furthermore, the temperature gradient caused by the heat produced by functioning diodes in turn affects the wavelength, as demonstrated in (III). Indeed, since $\mathbb{P}_{out}$ is coupled with $\mathbb{P}_{in}$ through the efficiency, wavelength extension severely impacts the resulting FLM power. This equation holds for emitted wavelengths up to 1 µm, where the wavelength dependent coefficient can be roughly approximated as a constant (0.3). Out of this range, incorrect KQC values can be observed, e.g. the lasers functioning in visible range.

$$\frac{\partial \lambda}{\partial T} = 0.3\ \frac{nm}{°\mathrm{C}} \qquad \text{(III)}$$

Two separate cooling systems are installed on the coldplate, where optimally selected components are mounted, to prevent overheating. Between each consecutive multi-emitter working, 1°C difference (∇T) is measured.

The FLM is split into multiple zones at the same temperature hinged on $numFLM$, the number of diodes used within the FLM, as shown in Figure 13. Combined with the temperature gradient given in (III) and 1°C of ∇T, The hotter zones comprise diodes operating with longer wavelengths compared to those observed at the reference temperature (T_{ref}).

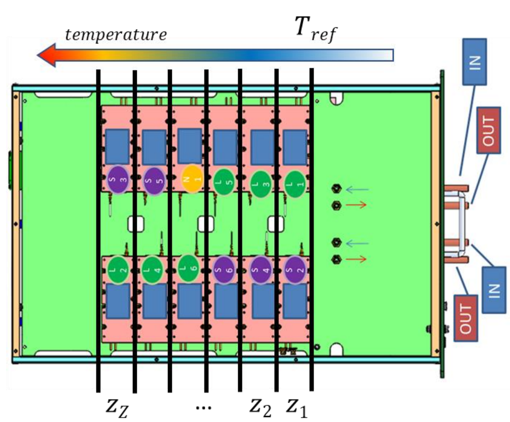


Figure 13. Fiber Laser Module (FLM) Zones

The formula that intercepts the number of zones (Z) with num_{FLM} to systematically compute the extended wavelength can be derived as given in (IV) and (V).

$$Z = \begin{Bmatrix} \dfrac{num_{FLM}+1}{2}, & num_{FLM} = 2k+1 : k \in \mathbb{Z} \\ \dfrac{num_{FLM}}{2}, & num_{FLM} = 2k : k \in \mathbb{Z} \end{Bmatrix} \tag{IV}$$

$$\bar{\lambda}_{c_{c,Z_z}} = \bar{\lambda}_{c_{c,Z_1}} + \frac{\partial \lambda}{\partial T} \times \nabla T \times (z-1) \qquad z = 2, \dots, Z \qquad c = 1, \dots, C \tag{V}$$

Based on this product meta-model, the Assembling Module selects the best combination of diodes currently available in the inventory in order to fulfil the desired target power, $\mathbb{P}_{target}$. The optimisation algorithm embedded inside the Assembling Module solves the following fourth order nonlinear optimisation problem with integer variables and nonlinear constraints.

$$Objective\ Function\ (O.F): min\ (|\mathbb{P}_{out}(\alpha) - \mathbb{P}_{target}|) \tag{VI}$$

subject to:

$$0 < \alpha^{opt} < N^{u}(\tau) \tag{VII}$$

$$\mathbb{P}_{out}(\alpha) \geq \mathbb{P}_{target} \tag{VIII}$$

$$\sum \alpha^{opt} \leq num_{FLM} \tag{IX}$$

As a result, the optimal selection vector α^{opt} with the size $C \times Z$ containing the selection of components from classes and their positioning in FLM is obtained. Then, this selection vector is converted to a matrix for an easy interpretation to the user.

$$\alpha^{opt} = \begin{bmatrix} \alpha_{c_1,z_1} & \cdots & \alpha_{c_1,z_Z} \\ \alpha_{c_2,z_1} & \cdots & \alpha_{c_2,z_Z} \\ \vdots & \vdots & \vdots \\ \alpha_{c_C,z_1} & \cdots & \alpha_{c_C,z_Z} \end{bmatrix}_{C \times Z}$$

6. Results

Classification algorithm, physics-based meta-model and optimisation tool are embedded in two software modules of a unique control unit.

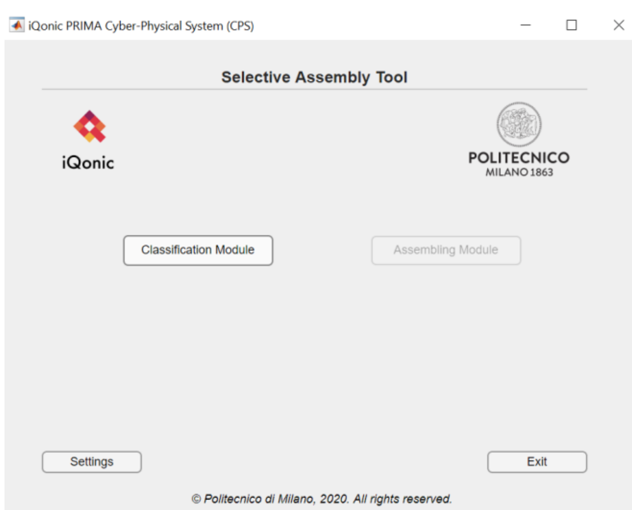


Figure 14. Control Unit Interface

Considering the travel restrictions during COVID-19 pandemic, since the actual assembly line of Prima Electro is located in Massachusetts, USA and hence the line stoppage must be planned well-timely in advance because of their tight production schedule, two virtual experiments have been arranged in this case study before in-situ testing and validation of proposed methodology. Based on the user-specified parameters and measured KQCs of the components, the method was initially tested in lab-scale. The parameters used for Classification and Assembling Modules are given in Table 1.

Table 1. Intelligent Modules Parameters

	Classification Module	**Assembling Module**
KPI	Power	—
LSL (W)	220	—
USL (W)	260	—
num_{FLM}	—	13
$\mathbb{P}_{target}$ *(kW)*	—	2.1

Here, given that the optimization aims to minimize the divergence from target power of 2.1kW, KPI for Classification Module is selected as *power*. Since the typical FLM efficiency is approximately ~70-75% (from Figure 12), the power of each multi-emitter to be assembled into FLM should be around 230W on average for *numFLM* = 13 (the configuration of product type used in this analysis), neglecting the correlational factors of wavelength and operating temperature. On the basis of this, *LSL* is selected as 220W, relatively closer to 230W than *USL*, 260W, since it is more critical to meet first the 2.1kW, then to exceed it.

The genetic algorithm (GA) is used to solve the optimisation problem. The specific parameters of GA are shown in Table 2.

Table 2. Genetic Algorithm Parameters

Migration Fraction	0.3
Crossover Fraction	0.8
Mutation Fraction	0.2
Migration Interval	20
Population Size	200
Elite Count	10

where,

- ***Migration fraction*** specifies the number of moving individuals between subpopulations.
- ***Crossover fraction*** is the population fraction that are generated by crossover of two parenting individuals, other than elites, from previous generation.
- ***Mutation fraction*** represents the mutated portion of a population that will be transferred to next generation.
- ***Migration interval*** defines how many generations pass between migration.
- ***Population size*** is the total number of individuals in each generation. Large population size allows the GA to search entire solution space, thereby increases the chance to find a global minimum rather than local minimum. On the contrary, a large population size significantly intervenes with computational load, causing the algorithm to run more slowly.
- ***Elite count*** are the individuals that are guaranteed to in the next generation.

Firstly, First-In-First-Out (*FIFO*) strategy, which is currently in-use at Prima Electro, is compared to the Selective Assembly with increasing number of classes (*C*) for 250 diodes in the inventory and their in-line power and wavelength measurements. FIFO is a common and rather outmoded heuristic compared to modern manufacturing methods, on the other hand due to the complexity of the described problem (high-order, non-linear optimization) and the absence of ZDM-driven smart algorithms capable of processing in-line gathered multi-layer information about products, processes and systems in a digital environment to solve it, FIFO is still used in optoelectronics industry. In FIFO, the diodes are sequentially assembled into FLM zones, whereas in selective assembly the parts are selected and assembled according to resulting CPS outcome. The results are compared in terms of mean deviation between the measured and target FLM power as shown in Figure 15.

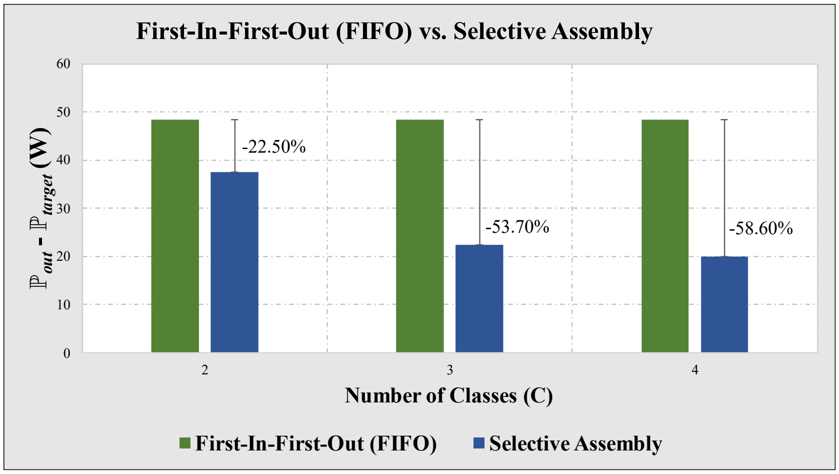


Figure 15. First-In-First-Out (FIFO) vs. Selective Assembly for increasing Number of Classes (C)

In comparison to FIFO, selective assembly's advantages are noticeable and become increasingly clear as the number of classes increases. The deviation from target power is reduced more than 50% for $C=3$ and $C=4$. In fact, increase in number of classes reduces the variations of mean KQCs within classes by narrowing down the class interval, which in turn enhances the effectiveness of selection procedure. Thus, the CPS-based approach has a particular role in product quality. In addition to that, it is observed that the marginal benefit of having higher number of classes declines after a certain point. This implies that the logistical complexity brought on by four or more classes does not compensate the quality improvement.

The second experiment involves the dynamic application of the proposed CPS-based approach. Particularly, FIFO and selective assembly strategies are analysed in four scenarios. Each of these scenarios is characterised by the production batches of increasing number of parts: 13, 26, 64 and 92. In FIFO, as soon as thirteen diodes are available in the buffer, an assembly operation is immediately performed. In selective assembly, the Classification Module initially classifies the arriving batch of parts into the three classes (as a result of previous analysis); and when all the parts have been classified, the Assembling Module is called. The results are given in Figure 16.

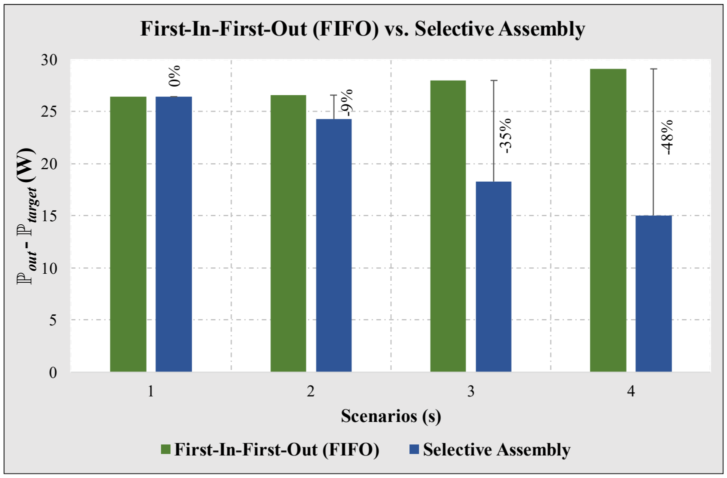
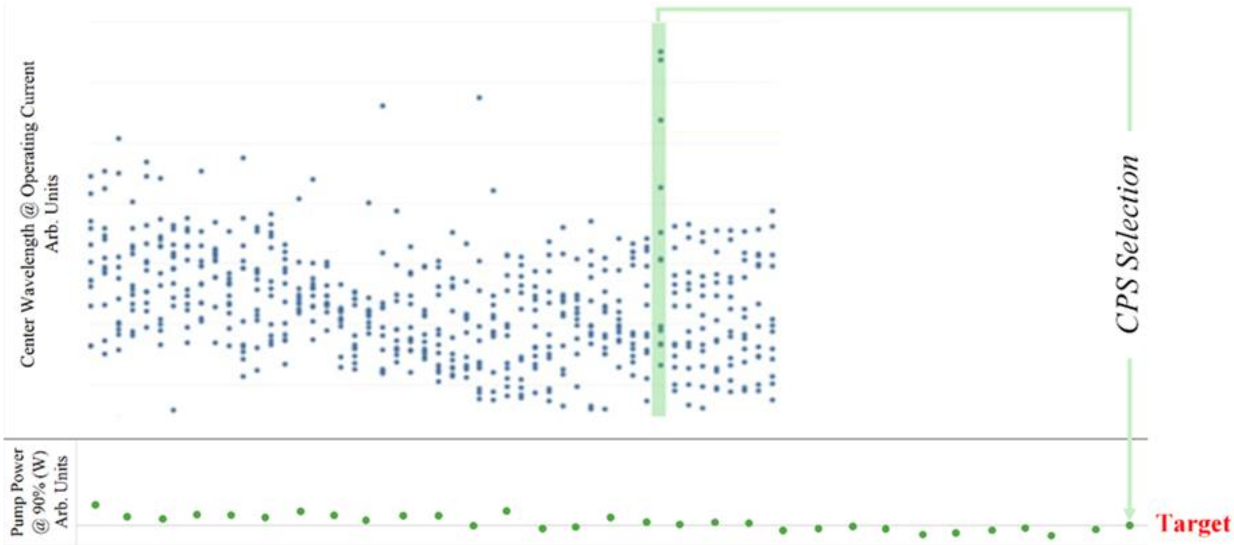


Figure 16. First-In-First-Out (FIFO) vs. Selective Assembly in Different Scenarios

Except for the first scenario (s_1), where no difference is observed, it is evident that the selective assembly is better than FIFO in every other scenario, where the gain varies between 9% and over 45%. This is explained as the Assembling Module selects more appropriate diodes from the available set of components present in buffers and provides an optimal positioning in FLM configuration. Waiting more parts in the buffer before activating the Assembling Module may improve the quality but it requires a larger buffer capacity, therefore generating a trade-off that needs a system-level analysis to be addressed.

Lastly, following the completion of virtual experiments, the final validation has been done on a dataset of 150 multi-emitters located in Massachusetts facility of Prima Electro. The selected products are shipped from diode fab in Italy and assembled in actual assembly line in Massachusetts. The results shown in Figure 17 demonstrate that the final power is on target and during the selection, a wider range of original wavelength has been selected. This is very promising, for a better use of the parts that are currently in an *on-hold* stock because considered at limit of the specifications, opening a new pathway towards reusability.



**** Data are omitted due to confidentiality***

Figure 17. CPS-based Selection Results

7. Discussions

In optoelectronics industry, where the final products are usually constituted by many small functional units to be able to handle the manifold individualization, the ultimate quality of an assembly vastly depends on transfer functions in-between the interacting pieces. The proposed function-oriented selective assembly methodology, *(i)* based on in-line inspected component characteristics, *(ii)* predictive defect prevention actions through feed-forward control, and *(iii)* physics-based product model for complex interactions between subcomponent and final assembly characteristics, dynamically finds the optimal set of components to be assembled in order to guarantee the customer-driven KQCs and functionality of the assembled product. The numerical results demonstrated in Section 6 support the effectiveness of CPS-based method in terms of higher product quality. The CPS is rigged with HMI to reckon human-in-loop paradigm to assist the user based on step-by-step approach. In as-is scenario, human actively participates in photonics production, but rarely supported by digital technologies (e.g. decision-support systems, virtual/augmented reality tools) offered by Industry 4.0 compared to other industrial sectors like automotive. In proposed CPS architecture, the operator is able to access the status of whole process-chain through digital tools and actuate the control actions in order to achieve ZDM. Indeed, the designed workflow aligns with the transitioning perspective from autonomous production lines where human is seen as a defect generation source towards human-centred manufacturing approaches in which human is the most valuable production asset.

It is interesting to notice that, when tactical decisions need to be taken at process-level, the lack of meta-models, neither physics-based nor data-driven, significantly increases the lead time. For instance, in real case study under discussion, the human gut feeling/expertise-based selection process takes between 15-20 min. depending on the inventory size. Instead, the total computational time requested by both CPS modules, *Classification* and *Assembling*, is around 3-5 min. (65-80% decrease). This means that the CPS-based approach enhances also the overall system-level performance.

The last but not the least, the KPI for two experimental setups are selected as *power*. This itself is meaningful, bearing in mind that the objective function in optimization problem is to minimize the excess power after meeting the $\mathbb{P}_{target}$. On the other hand, as discussed in Section 5, wavelength is the second, potentially equal-impactful, KQC that could be considered in the analysis. While it is not directly affecting the power, it acts on the final output FLM power through the efficiency. As a matter of fact, it has been observed from the consecutive runs that the tool tends to position the components with lower wavelength values *(< 976 nm*. which corresponds to peak efficiency point) into hotter zones of FLM to extend their wavelength to improve their efficiency. On the contrary, the components with a wavelength around 976 nm. or higher are placed in colder zones to avoid efficiency loss (*see Figure 12*). Inevitably, this phenomena perfectly aligns with the logic of operator who used to select and assemble the components from bins based on a similar idea before CPS. This time, instead, the knowledge is more structured and scientific, therefore more trustworthy, that results in lower decision-making time. To conclude, the selection of KPIs should be based on their relevance to the objective of the experiment. By analysing the remaining factors along with the chosen KPIs, it may be possible to further improve the efficiency and effectiveness of the conducted experiments.

8. Conclusions and Future Works

In this paper, a novel CPS-based selective assembly system for function-oriented production is proposed. The primary interest of the paper was to focus on virgin fields in optoelectronics industry with the help of ZDM techniques and emerging technologies of Industry 4.0 era such as Cyber-Physical Systems to improve final product quality. The proposed methodology can become a pioneer force to raise an awareness about the benefits of ZDM, rather than conventional ones, in sustainable, smart and waste-free production for optoelectronics industry and to attract more research and industrial communities to invest more time and effort into it.

Future research will include the extension of the approach for larger multi-stage systems characterized by longer process chains and more complex quality correlation paths. The optimal design of the CPS depending on the number of classes will be further investigated to systematically implement in industrial context. The CPS-based approach to manage in-line defects can be enwidened to cover value-retuning solutions from in-line waste and post-use products;

opening up unique opportunities towards circularity in flexible, dynamic and technology-intense industry. But, there are still several aspects to be resolved in advance: the lack of standardization, making it particularly demanding to reuse and recycle some of the materials, or the high-precision, high-quality demands in optoelectronics, mandating an intense effort to remanufacture an end-of-life product into its original specifications.

It is encountered that, in certain cases, some of the assembled multi-emitters may fail due to a short-circuit in connectors, damaging the assembled multi-emitter. These damaged components under this circumstance need to be replaced from inventory. As the algorithm, for now, is developed to optimize the solution for complete FLM with *numFLM* number of components, which is 13 in this case, the selection for only failed multi-emitters cannot be performed. This reduces the flexibility of the tool which will be addressed in the next released version (v1.2). Moreover, the product meta-model will cover also the other product type, GL-100-E, for low-specification applications ($\mathbb{P}_{target} < 1\ kW$) with higher number of components to be assembled. The performance of proposed methodology with other solutions than FIFO to the similar problem will also be compared to assess its validity.

Finally, this research is aimed to open up a new horizon for Zero-Defect Manufacturing (ZDM) solutions implementation in multi-stage optoelectronics production systems, relying on CPS, data-driven/physics-based/hybrid modelling and optimisation as Key Technology Enablers (KETs).

9. CRediT Authorship Contribution Statement

Ozan Emre Demir: Software, Writing – Original. **Marcello Colledani:** Conceptualisation, Methodology, Funding acquisition. **Roberto Paoletti:** Conceptualisation. **Giulia Pippione:** Writing – review

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