Cognitive Production Lines: Reinforcement Learning and Adaptive Intelligence for Real-Time Vehicle Assembly Reconfiguration in Industry 5.0

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Abstract

Smart Vehicle Manufacturing (SVM) plays a vital role in the fast-growing market of electric vehicles. A distinctive feature of these New-Generation Intelligent Connected Vehicles (NGICVs) is their software architecture. SVM uses a traditional Mass Customization assembly-line production mode. Unlike simple electric vehicle architectures, NGICVs require more diverse components and parts like traditional internal combustion engine vehicles, but these part shortages lead to serious line-stopping production issues. Building SVM systems based on traditional Mass Customization assembly-line modes cannot solve this problem.

To overcome these issues, Smart Vehicle Manufacturing paradigms that adopt Adaptive Assembly Lines (AALs) are proposed. An Adaptive Assembly Line (AAL) is a fundamentally new assembly-mode paradigm that enables real-time assembly-line adaptation and mass customization of various part configurations according to real-time market demands in Smart Vehicle Manufacturing. AAL architecture drastically changes each stage of the Smart Vehicle Manufacturing assembly process. SVM systems have deployed data architecture supporting these Smart Vehicle Manufacturing paradigms. The developed data governance framework with in-depth data perception enables high-quality data generation for AI-driven Adaptive Assembly Line system performance improvement.

Keywords: Adaptive assembly line, AI data infrastructure, machine learning, next-generation vehicle manufacturing, perceptual systems, optimal scheduling, predictive maintenance, operator support, human–machine collaboration, threat modeling.

1. Introduction

Next-generation smart vehicle manufacturing focuses on human-centric integrated production systems using both cyber-physical and virtual spaces to enhance safety, quality, efficiency, flexibility, and sustainability. Combined with service-oriented, smart-well, and assembly 4.0 paradigms, adaptive assembly architectures help fulfil these requirements. However, the growing complexity demands innovative solutions including AI-based human–machine collaboration for efficient knowledge acquisition and utilization. New technologies demand real-time perceptual systems and data infrastructures for quality assurance and secure operation of cyber-physical systems, as well as mitigation of cyber and physical threats. These aspects are crucial for real-time scheduling and dispatch, predictive maintenance, and fault diagnosis.

This section introduces the conceptual framework, emphasizing supporting paradigms and the related data, computational methods, physical elements, and security concerns for real-time optimization of adaptive assembly environments. Owing to the nature and diversity of contributing factors, development is best approached through dedicated subdisciplines, with integration ensuring reliability and utility. Therefore, innovation in automobile manufacturing is urgently needed. Adopting next-generation intelligent assembly lines that conform to the evolution trend

of vehicle products has become an important strategy for automobile manufacturers to take the initiative in competition and create explosive growth points at the early stage of market demand.

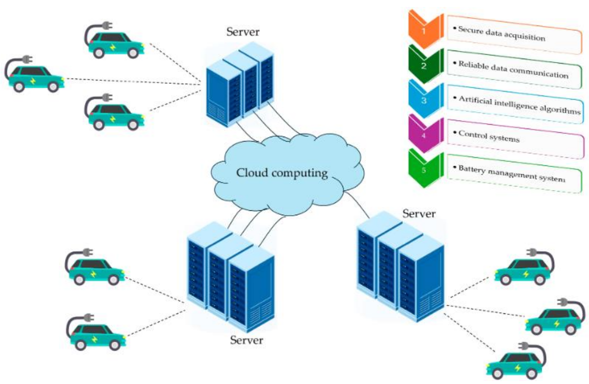


Fig 1: Next Generation of Electric Vehicles

1.1. Background and Significance

Real-time, data-driven AI methods drive rapid decision-making and minimize human involvement in highly repetitive tasks. Contrasting roles require new human–machine collaboration frameworks to harness individual strengths while allowing specialization in different areas, with implications for the education and training of future assembly line workers.

The automobile manufacturing industry is undergoing intense transformation, driven by changing market demands and the rapid development of new intelligent products and technologies. In the next five years, the number of advanced driver-assistance systems (ADAS)- or automated driving-enabled smart vehicles in the world's major automobile markets is expected to increase by 60% to 100%. The growing popularity of smart vehicle products has led to increasingly stringent functionality, quality, safety, and other performance requirements for automobile manufacturing. Traditional mass production paradigms are increasingly challenged by small-batch production, frequent switching of production lines, increased complexity of assembly processes, and other new requirements.

Equation 1: Real-time scheduling objective: minimizing idle time

1.1 Notation (single bottleneck station)

- Jobs (vehicles) indexed by $j \in \{1, \dots, n\}$
- Processing time: p_j
- Release/availability time (job can start only after it arrives from upstream): r_j
- A sequence (permutation): $\pi = (\pi_1, \dots, \pi_n)$
- Start time: S_{π_k}
- Completion time: $C_{\pi_k} = S_{\pi_k} + p_{\pi_k}$

1.2 Recurrence for start times (step-by-step)

For the first job in the sequence:

$$S_{\pi_1} = \max(0,\ r_{\pi_1})$$

For every next job $k \geq 2$:

$$S_{\pi_k} = \max(C_{\pi_{k-1}},\ r_{\pi_k})$$

because:

1. the machine must be free: start $\geq C_{\pi_{k-1}}$
2. the job must be available: start $\geq r_{\pi_k}$
3. The earliest feasible start is the maximum of those two.

1.3 Idle time definition and objective

Idle before job π_k:

$$I_{\pi_k} = \max(0,\ r_{\pi_k} - C_{\pi_{k-1}})$$

Total idle time:

$$I(\pi) = \sum_{k=1}^{n} I_{\pi_k}$$

(with $C_{\pi_0} \equiv 0$ for convenience)

Optimization problem:

$$\min_{\pi} I(\pi)$$

This matches the paper's stated goal of minimizing idle time.

1.4 "Minimal-remainder-time" heuristic (formalized)

The paper mentions "remaining execution time … considered as hidden time" and "minimal-remainder-time heuristic rules".

A practical formalization at decision time t:

- Let $\mathcal{A}(t) = \{j : r_j \leq t\}$ be available jobs.
- Let $R_j(t)$ be *estimated remaining time to finish job* j (could be from digital twin / sensing).

Then the heuristic is:

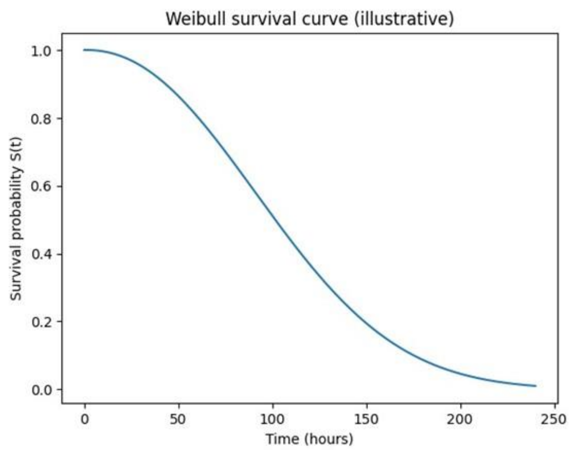
$$j^*(t) = \arg\min_{j \in \mathcal{A}(t)} R_j(t)$$

A simple proxy is $R_j(t) \approx p_j$ (shortest processing time first).

2. Conceptual Framework

The conceptual framework encompasses both cutting-edge smart vehicle manufacturing paradigms and innovative adaptive assembly line architectures. At the manufacturing level, vehicle electrification, automated driving, shared mobility, and connectivity are transforming conventional automobiles into intelligent systems for smart cities. Smart vehicle manufacturing must satisfy both changing consumer preferences for highly customized products and the classic requirement for scale economies. The integration of data-driven processes with AI supports personalized production by providing traditional discrete manufacturers with industrial-strength customization capabilities. Adaptive assembly lines featuring dynamic changes in both product types and resource capacities, however, enable customization absolute by supporting modifications of the products themselves. Dynamic multi-skill workers with real-time work instructions drawn from a digital twin of the factory are critical for ensuring agile connections between production stages.

The data infrastructure must also support the real-time processing of data from diverse sources with strong time constraints while guaranteeing high data quality. Multiple perceptual systems must be deployed across the entire factory to cover all aspects of data collection and processing for a broad range of AI applications, from generic tasks to specialized niche areas. These include intelligent cyber-physical processes for real-time scheduling and dispatch, predictive maintenance and fault diagnosis, and the dynamic enabling of human–machine collaboration for advanced human–machine synergy. A well-designed AI-Human-Technology interface with appropriate visualizations for operators increases trust and engagement while enhancing performance and reducing errors. Trust also influences acceptance and adoption, and explainable and interpretable AI methods promote user acceptance by increasing understanding of underlying mechanisms and processes.



2.1. Smart Vehicle Manufacturing Paradigms

Smart vehicles are already ubiquitous on the road, yet most prototypes are still manually made, like traditional automobiles. The era of smart manufacturing should make it possible for smart vehicles to mainly include next-generation automotive, aerospace and marine products can be fully adapted, that is, the expected production capacity, market demand, target specification and assembly are spontaneously matched by self-organization or self-adaptation according to assembly delivery plans matching neural networks. While traditional smart traffic plans primarily adopt high quality traffic light use integrated Smart Signal , next-generation products require high-quality divide-and-conquer plans, add optimal resampling points such as near-parallel stop for motorization, tinning for automatic welding, processing clearance and quarter etc by integrated multi-level interactive swarm intelligent-based Traffic Simulations and Quality Assessment Software, supporting clusters of intelligence preparing in advance for sudden changes of uncontrolled and so on.

To achieve main line assembly delivery, Adaptive assembly lines and corresponding smart synchronous technology are key tasks. Intelligent responding adaptive assembly lines allow designed, market-directed, planned and deployed rule-based parallel assembly cells in selected modules. Such technology is also applicable to conventional alternative traditional assembly factories and shipyards or complete manufacturing plants featuring artificial intelligence intelligent-built detection and detection relaxing sliding fast Alternative transportation can be towards alternative partitions in the horizontal or vertical direction.

2.2. Adaptive Assembly Line architectures: Adaptive assembly line architectures integrate operation-specific task allocation and equipment selection to enhance service flexibility and efficiency on a virtual line in practical operations. The complexity of process design generally increases with the new product process cycle. Current design methods often ignore product realization feasibility and neglect the description of a virtual assembly line. Furthermore, specific operation allocation and physical facilities assignment are weakly related to service performance.

A simplified assembly line constructed from operation-level component assemblies, combined with practical engineering know-how, provides an effective solution. The proposed method defines two separate groups connecting the digital twin. The first group generates a referential product realization process with a physical assembly line structure, while the second group deterministically allocates assembly functions related to the products' magic component. Control points guide the second stage component assembly with no physical buildup. The virtual assembly improves flexibility and reduces transit time while maintaining quality requirement compliance.

Equation 2: Dispatching with travel time (worker assignment)

2.1 Notation

- Workers $w \in \mathcal{W}$
- Tasks/jobs $j \in \mathcal{J}$
- Travel time from worker w to job j: τ_{wj}

- Service/processing time if worker executes it: p_{wj} (can include skill effects)

2.2 Basic assignment objective (one job at a time)

If dispatching decides "who should do the next job j":

$$w^* = \arg\min_{w \in \mathcal{W}} (\tau_{wj} + p_{wj})$$

This is exactly "travel + execution".

2.3 Full assignment as optimization (batch)

Binary decision variable:

$$x_{wj} = \begin{cases} 1 & \text{if worker } w \text{ assigned to } j \\ 0 & \text{otherwise} \end{cases}$$

Constraints (each job assigned once):

$$\sum_{w \in \mathcal{W}} x_{wj} = 1 \quad \forall j$$

Objective (minimize total travel service cost):

$$\min_{x} \sum_{j \in \mathcal{J}} \sum_{w \in \mathcal{W}} x_{wj} \left(\tau_{wj} + p_{wj}\right)$$

3. Data Infrastructure and Sensing

A Next-Generation Smart Vehicle Manufacturing Adaptive Assembly Line needs a connected data infrastructure to guide real-time AI-driven optimization of all production functions across the entire life cycle. Data supports real-time scheduling, predictive maintenance, and digital-twin-enabled risk management—all critical to making the Adaptive Assembly Line work as intended. Data are collected and processed by an integrated set of sensors for factory-wide monitoring of equipment status, product quality, workmanship, materials availability, stock level, workforce performance, and the production environment. Five primary functions enable data-driven process optimization: perception through adaptive sensing; digital twin integration; data governance; data quality assurance; and search and service support.

To ensure real-time nonlinear optimization, the information supply must feed the task-allocation and disturbance-sensing models that govern the continuous automatic and synchronic resetting of process schedules. Robust perceptual support requires the deployment of a Digital Twin for a Next-Generation Smart Vehicle Manufacturing Adaptive Assembly Line—a comprehensive replica of physical assets, processes, and states—that permits machine-vision testing during assembly and at end of line. Vigilant monitoring of production equipment clarifies whether failures are imminent or are occurring. Random or unanticipated failures detected first by local measures need third-party confirmation before triggering maintenance and repair interventions. To remove human error as a failure cause, training and assistance systems support workforce task execution, monitor work quality, and suggest timely corrective action when quality slackens.

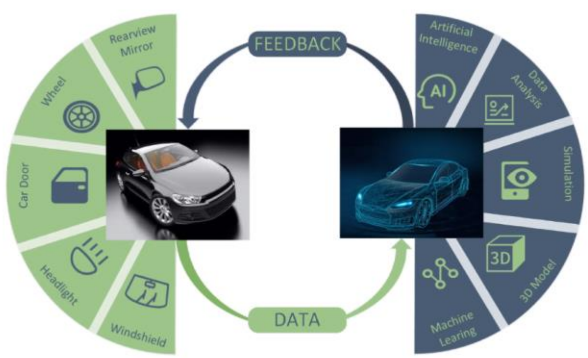


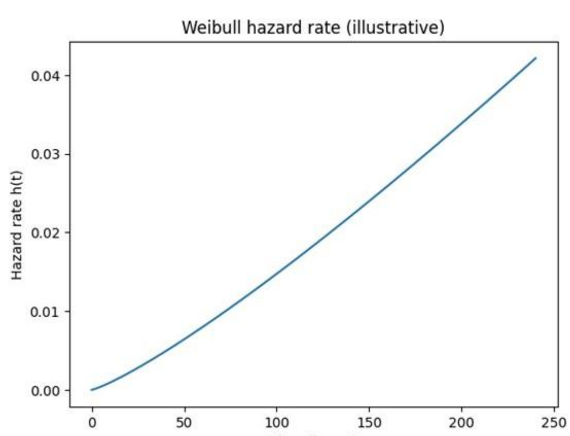
Fig 2: Data Infrastructure and Sensing

3.1. Perceptual Systems and Digital Twin Integration

Data-driven process optimization relies on a rich pool of real-time, high-quality data obtained by a variety of perceptual systems. Emerging technologies, such as lightweight sensors, low-cost cameras, and digital twins that

track both physical and logical identities, offer new opportunities to gather such data. Low-cost cameras used for quality assurance can be repurposed not only for production monitoring but also for operators' skill assessment and process-related predictions, such as potential assembly-quality defects or downtime due to operator misconfiguration. Cooperation between virtual twins and real-time sensing systems enriches the physical system's knowledge base, thus enabling more-informed control and adaptive optimization of the real-time assembly-line-dispatch process.

Various process-monitoring technologies, such as digital twins, model-based systems engineering, and deep learning methods for quality prediction allow multiple process aspects to be monitored, controlled, and optimized in real time. For example, anomalies, malfunctions, and capacity issues of the assembly line can be diagnosed through a hybrid cloud-edge voice control system that supports predictive maintenance. Knowledge from the perceptual system can even be transferred to the logical layer to address optimizations in the production-sequencing process. Proactive and predictive perception replaces reactive perception, which can in turn unlock advanced applications, such as intelligent assembly-line dispatching that improves workloads and demand balance among operators.



3.2. Data Governance and Quality Assurance

The sheer volume of data generated by industrial facilities and supply chains necessitates strict data governance policies and processes for firms to exploit their data effectively. Although deep learning and general AI enable the use of unlabeled data, quality continues to be a major barrier to the successful deployment of AI. Data management encompasses data collection, preparation, processing, storage, sharing, and use, covering everything from supporting the flow of data between sensors and data lakes to ensuring high-quality labelled datasets for supervised learning and safety-critical tasks. Establishing provenance is key to ensuring and assessing the quality of operational data. History-aware processing enables greater insight into the reliability, completeness, and accuracy of data by considering the information contained in the entire temporal history of the data. Data quality plays a key role in success or failure, especially for real-time and mission-critical AI applications, and automation is needed to create the annotated datasets required for supervised learning. Factors influencing operator perception of data quality should also be considered, and research is required on the role of ontology-based reasoning for quality assurance. Establishing data governance policies can also help manage the use of open datasets.

Critical to successful machine replication is ensuring the consistency of all data stores in a distributed environment. Although consistency can often be sacrificed in non-mission-critical applications, it remains crucial for real-time and safety-critical automation. Self-organizing systems can address consistency challenges with limited processing effort, without demanding synchronization input from the entire system. Such consistency limitations also need to be supported in distributed learning algorithms, and research remains necessary into ensuring distributed data replication meets the needs of selected applications. Indeed, data management support for general AI-enabled cloud services remains an open research area.

4. AI Methods for Process Optimization

Next-generation smart vehicle manufacturing needs systematic methods to reduce latent idle time and enhance overall efficiency. AI can help, especially because most assembly process data are captured or could be recorded by industrial Internet of Things sensing devices. AI applications include real-time scheduling and dispatching, predictive maintenance and fault diagnosis, and process control based on reinforcement learning.

In assembly line systems, real-time scheduling selects sequences for products that share the same working station with the objective of minimizing overall idle time of key resources. The remaining execution time until the next triggered batch at a working station should be considered as practically hidden time. Related minimal-remainder-time heuristic rules can also account for the assignment of products to assembly lines within a multi-line system. Task dispatching allocates product batches, determined by a high-level scheduling level, to workers in a way that takes additional travel time into consideration.

Equation 3: Predictive maintenance: Remaining Useful Life (RUL)

3.1 Reliability definitions (step-by-step)

Let failure time be random variable T.

4. **Survival function**

$$S(t) = P(T > t)$$

2. **Probability density**

$$f(t) = \frac{d}{dt}\big(1 - S(t)\big) = -S'(t)$$

3. **Hazard rate** (instantaneous failure rate given survival up to t)

$$h(t) = \frac{f(t)}{S(t)}$$

3.2 Weibull model (common for industrial components)

If $T \sim \mathrm{Weibull}(k, \lambda)$ (shape k, scale λ):

$$S(t) = \exp(-(t/\lambda)^k)$$

Differentiate:

$$f(t) = \frac{k}{\lambda}(t/\lambda)^{k-1}\exp(-(t/\lambda)^k)$$

Then:

$$h(t) = \frac{f(t)}{S(t)} = \frac{k}{\lambda}(t/\lambda)^{k-1}$$

3.3 Mean residual life (a clean "RUL" formula)

If current age is t_0, then:

$$\mathrm{RUL} = \mathbb{E}[T - t_0 \mid T > t_0]$$

Using survival:

$$\mathbb{E}[T - t_0 \mid T > t_0] = \int_{t_0}^{\infty} \frac{S(u)}{S(t_0)}\, du$$

This is a standard way to compute RUL once the twin/AI estimates $S(\cdot)$ under current conditions.

4.1. Real-Time Scheduling and Dispatch

The current assembly scheduling methods are usually based on production planning. Production planning determines when x vehicles of a certain type and configuration must be produced within a defined time frame. Given this early information, the assembly scheduling chooses one of the possible configurations to produce at each stage. This process lacks consideration of real-time information and dispatch scenarios. Real-time scheduling addresses the issue of scheduling the assembly process based on current information of the assembly line (e.g., the progress of each line; the completion time of vehicles in the previous stage; etc.) The assembly line execution time is minimized by dynamically dispatching vehicles to different configurations (depending on their levels of completion) that are detected as

the fastest to finish next. In real-time scheduling, there are three tools working in conjunctions: a detection function, a decision function and a dispatch function.

The real-time dispatching of assembly lines will never grow in importance due to increasingly volatile markets. More variants, lower batch sizes and shorter life cycles produce a higher demand for more flexible, reconfigurable assembly lines. These smart assembly lines define an architecture that enables the assembly of a set of similar products and that supports real-time adaptation of the resource allocation during execution. Scheduling methods for static problems, where the configuration of the assembly line is fixed at planning time, have already been proposed for those flexible assembly lines. However, they remain too few for the real-time mode.

4.2. Predictive Maintenance and Fault Diagnosis

Data generated by the perceptual systems can be employed not only for operational optimization, but also for maintenance forecasting or fault detection and diagnosis. Such AI applications directly enhance the reliability of manufacturing systems and their resilience to external threats. New computing models, such as digital twins, provide rich real-time information for predictive maintenance by estimating the health state of physical subsystems and predicting its future evolution. Combining this information with knowledge about operating conditions helps to compute the remaining useful life for each subsystem, enabling condition-based maintenance and more efficient management of service resources.

Digital twins can also be exploited for fault detection and diagnosis, for example by modelling (using a physics-based approach) the fault-free system and monitoring the residual errors. These errors can then be classified so that the most likely fault can be identified. A hybrid approach integrates the fault information with data-driven techniques powered by deep learning algorithms trained on the historical datasets of the system's operational conditions (sensing data, alarm data, operator interventions, etc.) to detect fault signatures and their associated operating conditions and to diagnose the underlying causes. Deep transfer learning is further applied to reduce the amount of data required for training.

5. Human–Machine Collaboration and Workforce Implications

Novel interactions between humans and machines are being established on smart connected assembly lines. On one hand, some operators are working collaboratively with collaborative robot arms, and the intelligence of these robot arms requires training by actual operators. On the other hand, operators are no longer carrying out repetitive operations such as T-po or pin insertion, which are common in traditional assembly lines. Instead, their roles have evolved towards coordination, supervision, quality control, and resolving exceptions.

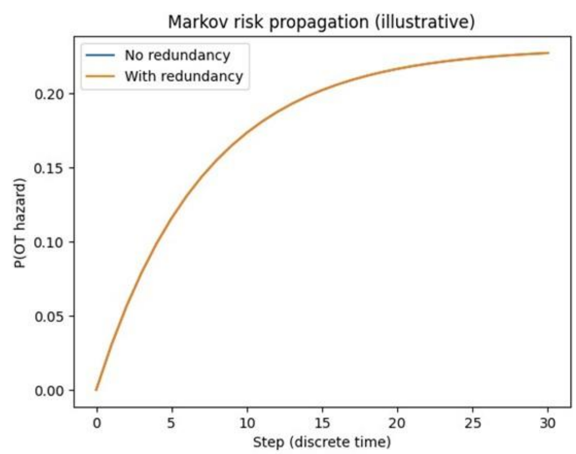
New operator interfaces such as Google Glass are being introduced to superimpose necessary instructions on real scenes for operators to enhance operational accuracy and efficiency. Meanwhile, the analysis of human–computer interaction based on explainable artificial intelligence has attracted more attention, and an increasing number of AI-scheduling algorithms can provide clearer explanations and reasons for scheduling decisions, helping operators to understand, accept, and trust decisions made by the system. During the transformation to smart manufacturing, the skills required for workers no longer focus on single-task proficiency but integrate multi-tasking capabilities, knowledge, rich experience, and even creativity. As a reservoir of knowledge and skills, operators will need continual retraining to maintain their store of knowledge and further prepare for potential skill transformation in the future.

Fig 3: Human–Machine Collaboration and Workforce

5.1. Operator Interfaces and Interpretability

Modern assembly lines that include collaborative robots should provide human workers with easy-to-interpret quality assurance information that is understandable and actionable so they can respond quickly and safely. Operator interfaces should be multi-sensory and easy to interpret, delivering tailored notifications and information through multiple modalities – such as visual, auditory, tactile, and olfactory – so that cognitive overload does not take place. For instance, a holistic surround view can provide nearby operators with adjacently displayed visual and auditory alerts to seek nearby defects without searching through a visual display. A dog-bark-like notification can wake an operator from a state of drowsiness when approaching a danger zone. A source-directing tactile alarm can alert an operator when a defect needs immediate attention. In addition, vital machine state information should be transmitted from machine to operator so the operator can comprehend the reasons for an alert. Interpretability of AI tools in predictive maintenance and fault diagnosis must be prioritized to build user trust and satisfaction.

The direction of skill transformations and training requirements at the workforce level will change in next-generation assembly lines. Skill training requirements will become broader for the human workforce. The ability to continuously learn and adapt to changing task requirements will be the most important trait for future human workers. In collaborative environments, they will require knowledge to supervise the behavior of a collaborative robot and understand its programming parameters. Operators will need to understand machine-health indicators to act and react accordingly to maintain production safety and quality. Skills to monitor machine-health indicators and analyses service-history records will add value to their work in the future.



5.2. Skill Transformation and Training

Task-oriented approaches to skill development and training must adapt accordingly. On the one hand, assembly tasks will require less manual skill, given the availability of robotic systems. On the other hand, operators will increasingly perform tedious, dirty, or dangerous processes in collaboration with robots, necessitating their upskill and reallocation. For instance, robots equipped with AI-based perception systems may assist operators in the assembly of large components for heavy trucks, advising on the ideal position based on augmented-reality systems and some active guidance. Thus, intuitive operator interfaces ensuring trust and cooperation between humans and robots must be developed. On the AI side, methods capable of interpreting their recommendations, predictions, and decision processes to different extents are crucial to allow such training-aware systems to be easily acceptable for human operators.

Furthermore, the accessibility of AI decision-support systems also opens opportunities for training-based task collaboration. For example, the assembly of novel, complex, and expensive components—such as those with embedded sensors and drives—by lower-skilled operators in factories requires extensive skill development for both cost and risk reasons, particularly if local production is the goal. In such cases, AI systems can recommend assembly steps and solutions for tasks that were never previously performed, thereby adding interpretability and decision support toward the company-wide manufacturing. In addition to risk flow, redundancy mechanisms that appear in practice are also modelled. These redundancy mechanisms can compare to strengthen resilience but also decrease risk under certain conditions.

Equation 4: Fault detection & diagnosis via residuals (digital twin)

4.1 Residual definition

Let:

- measured sensor output: $y(t)$
- digital-twin predicted output: $\hat{y}(t)$

Residual:

$$e(t) = y(t) - \hat{y}(t)$$

4.2 Detection rule (thresholding)

Compute a scalar residual energy over a window W:

$$E(t) = \sum_{\tau=t-W+1}^{t} e\,(\tau)^2$$

Decision:

$$\text{alarm at } t \quad \Leftrightarrow \quad E(t) > \gamma$$

where γ is a chosen threshold (often from "normal" historical data).

4.3 Diagnosis (classification)

Create feature vector from residuals:

$$\phi(t) = [E(t),\ \max|e|,\ \text{spectral peaks}, \ldots]$$

Then classify fault type:

$$\hat{c}(t) = \underset{c}{\operatorname{argmax}} P\big(c \mid \phi(t)\big)$$

This matches the article's "residuals → classify → identify most likely fault" pipeline.

6. Cyber-Physical Security and Reliability

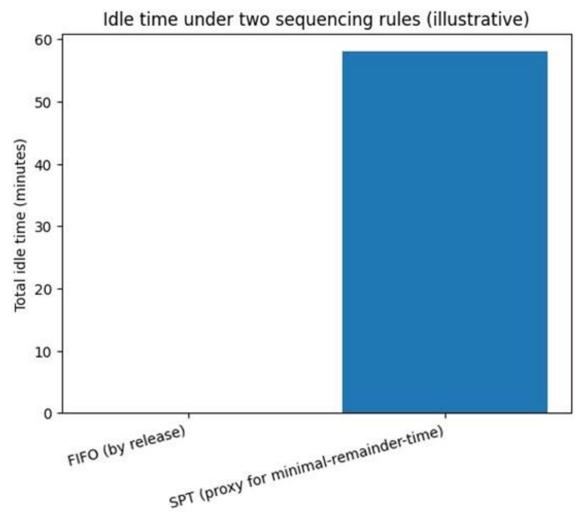
As modern manufacturing systems are innovatively transformed using advanced cyber-physical technologies, novel cyber-physical security risks emerge that can compromise process controllability and reliability, leading to safety issues for human operators and consumers. Although information technology (IT) security has been extensively studied and deployed over the last twenty years, few studies have investigated the integrated risk of IT security failures on related operational technologies (OT) in real-time control and subsequent impacts on business processes. Therefore, a cyber-physical security framework for smart vehicle manufacturing is presented to achieve a comprehensive understanding of potential threats in a real-time and dynamic context.

Most risk models view IT and OT as isolated systems. Although the differences between these systems indicate an orthogonal relationship, simply eliminating this assumption does not explain the origination of risk propagation. Security failure in IT contributes a new threat to OT, whose existence is not independent but contingent upon the status of IT.

6.1. Threat Models and Risk Mitigation

A cyber-attack constitutes the malicious disruption of the operation of a CPS. The failure of a CPS brought by such disturbances usually causes severe financial loss and even casualties. Therefore, security design is one of the most significant components of a CPS. Threat models are usually defined to identify the capabilities of possible attackers, and the risk occurrence and impact of these attacks on CPS are assessed. For Smart vehicle Manufacturing, these threat models include Denial of service (DoS), attack in operation, physical breach, service Providers threat, insider threat, information theft. DoS attack (UDP flood and ICMP echo flood) has the most severe impact, followed by attack in operation (deceiving CPS command). However, the risk of DoS is low.

DoS attacks usually take advantage of the wide vulnerability of service nodes. For the manufacturing system, suppressing DoS requires a uniform flow control (e.g., ingress rate limiting, anti-DDoS system) at the border routers/firewalls. Sensors are easily deceived, but safety-critical actuators are usually protected (e.g., the brake). Seldom can sensors/regulators rather than executors support failsafe schemes to resist attack in operation. Therefore, a reliable redundant structure is beneficial, based on risk impact assessment.



6.2. Resilience through Redundancy and fail-Safe Design

Redundant components can help mitigate the effects of cyber-physical attacks, while robust design can make systems less vulnerable to misbehavior. Advances in AI and AI-supported CPS systems are poised to achieve remarkable improvements in productivity, safety, and resource savings. However, the ultimate goals and methods must be reviewed critically and openly to identify areas of concern, reconsider unresolved issues, and avoid unforeseen future problems. The real and fully fledged application of CPS systems in complex, changing, and unpredictable environments will require further developments in many new and existing fields. In this respect, the growing and still rapidly changing range of applications will generate risks and problems that test the most advanced SI and require rethinking to achieve human-Machine integration.

The horizon of AI-supported CPS presents opportunities that mirror the dimensions of the global challenge: physical-vital-societal. The transformation of the economy represented by the fourth industrial revolution embraces these three dimensions. The pursuit of rapid attainment of the targets set for this systemic and shared transformation also urgently requires consideration of the implications on

every level of these achievements. The potential of advanced AI-supported CPS systems calls for extraordinary and unprecedented individual and collective responsibility and commitment. The core issues of new technologies for society represent both the challenge and the opportunity for their real and safe application.

Equation 5: Cyber-physical risk propagation as a Markov process (+ redundancy)

5.1 Markov chain basics

Let system state at discrete step t be X_t taking values in a finite set of states $\{1, \dots, m\}$.

Markov property:

$$P(X_{t+1} = j \mid X_t = i, X_{t-1}, \dots) = P(X_{t+1} = j \mid X_t = i)$$

Transition probabilities:

$$P_{ij} = P(X_{t+1} = j \mid X_t = i)$$

Transition matrix P has rows summing to 1.

State probability row-vector π_t evolves as:

$$\pi_{t+1} = \pi_t P$$

So after t steps:

$$\pi_t = \pi_0 P^t$$

5.2 Two-layer IT/OT coupled state (one clean construction)

Because the paper discusses IT impacting OT, build a joint state:

- IT status $I_t \in \{0 \text{ secure}, 1 \text{ compromised}\}$
- OT status $O_t \in \{0 \text{ normal}, 1 \text{ hazard}\}$

Joint state $X_t = (I_t, O_t) \rightarrow 4$ states total.

Then you design transitions so that:

- IT compromise increases probability of OT hazard
- redundancy reduces hazard probability and/or increases recovery probability

7. Conclusion

Traditional automotive assembly lines suffer from low operational flexibility and efficiency. In recent years, a number of innovative paradigms and concepts, such as smart vehicle manufacturing, adaptive assembly lines, data-driven perceptual systems, cyber-physical security, process optimization methods and human–machine collaboration, have been proposed. Although many automotive OEMs and their suppliers have established large-scale test beds within these respected domains, their full integration into modern production and business processes is still in a relatively primitive phase. Specific studies on the adaptation of AI-driven smart vehicle data paradigm and technologies in a next-generation automotive assemble ecosystem are extremely scarce.

Investigating the integration of these advanced technologies in a holistic and mutually beneficial way and gradually deploying the capabilities obtained by the fusion of these technologies into actual product and production practices, will support further generalization of the technologies and their upgrading to the next level. Advancing Smart Vehicle Manufacturing and its upstream and downstream progressed partners, these initiatives will significantly promote manufacturing industry transformation for carbon neutrality.

7.1. Emerging Trends

Recent developments in artificial intelligence (AI) and vehicle electrification have opened doors for new paradigms in smart vehicle manufacturing. A holistic, whole-system methodology is proposed that applies current and emerging AI technologies across the entire assembly line process; hence a special focus on adaptive assembly lines. Like their smart product counterparts, self-driving smart vehicles

emerge from an intrinsically digital environment, which spans the whole product lifecycle. Consequently, manufacturing is a data-driven process, supported by digital twins. All line processes are endowed with sensory and perception capabilities that enable self-awareness and the anticipation of dynamic perturbations, making real-time, short-term decisions through online data room management.

Perception and digital twinning together create the necessary data foundation for supporting AI models for real-time-scheduling/dispatch, predictive-maintenance/fault-diagnosis, and the corresponding models for machine learning in human–machine collaboration. The smart manufacturing ecosystem of people, vehicles, support functions, and shop-floor systems all interact and change in a dynamic environment. Real-time, deterministic AI technologies govern immediate-response operations such as dispatching, while long-term-sensing, pattern-recognition AI technologies govern predictive functions. Together, they enable transformative shifts in skills and training in all roles.

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