# Frameworks for Continuous Learning and Knowledge Updating in Dynamic AI Systems: Foundations, Methods, and Applications in AI-Enabled Intelligent Engineering Systems

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**ABSTRACT**

The dynamic environment in intelligent engineering system needs an AI framework that can learn and update its knowledge at any time, so that it can run normally even when the situation changes. Based on system engineering theory, network physical system (CPS) principle and information theory, this review discusses the framework to help adaptive AI combine physical processes with computational intelligence. An important theoretical basis says that you must adapt to feedback and measurement uncertainty to manage changing data. Methods include continuous learning strategy, concept change detection, intensive learning for dynamic optimization, gradually adaptive computer vision, and rapidly updated edge calculation. We show practical application cases in intelligent manufacturing and intelligent infrastructure, and find that it improves the operation intensity and the accuracy of prediction. The key analysis shows that there are great benefits, such as less downtime and more system autonomy, but there are also problems, such as disastrous forgetting, a lot of calculation, and the risk of instability in important cycle safety. An initial idea is to use a boot-based trigger mechanism in the CPS feedback architecture to better choose when to update and how to use resources. The conclusion of the review is that we need to create a standard and reliable adaptive framework so that the evolution of artificial intelligence can meet the needs of engineering systems throughout their life cycle.

**Keywords:** Continuous Learning; Lifelong Learning; Digital Twins; Cyber-Physical Systems; Concept Drift; Knowledge Updating; Intelligent Engineering Systems; Edge Computing.

## 1. INTRODUCTION

Intelligent engineering systems, such as intelligent manufacturing, infrastructure network and autonomous operation, operate under dynamic conditions such as machine wear, demand change, environmental change and component interaction. In these cases, the static AI model will soon become very bad, so the system needs to constantly learn and update knowledge, keep what is already known and learn new things. Systems engineering theory helps us to regard these systems as a whole connected with emerging behaviors, in which feedback loops allow adaptation. Network physical system theory explains how computer models and physical processes are interrelated, and real-time constraints and two-way information exchange make them develop together. Information theory supplements all this by measuring uncertainty, information quantity and information quantity, so as to help us update our knowledge effectively, avoid duplication and maintain the maximum predictive value.

The proliferation of sensor networks and digital twins has accelerated the deployment of AI in these fields, but the traditional batch training model cannot adapt to distributed displacement. The continuous learning paradigm solves this problem by reducing routinization, replay mechanism or architectural plasticity [1] Integration with CPS architecture can ensure that model updates conform to physical invariance and security. This review brings together theoretical subversion, method innovation and domain application, while maintaining a good balance between revenue performance and inherent risks. The structure ranges from basics to enabling technologies and illustrated cases, and then challenges and prospects. It provides a primitive synthesis and expands the adaptation of CPS feedback principle and information theory to control resource efficiency.

## 2. THEORETICAL FOUNDATIONS: SYSTEMS ENGINEERING, CYBER-PHYSICAL SYSTEMS, AND INFORMATION-THEORETIC UNDERPINNINGS

System engineering regards intelligent engineering system as a layered thing with goals. Their survival depends on the coordination between the target and the environment. Feedback control loops are very important in system theory. They help to understand how AI adapts: sensor data is the output of the system, the model performs control operations, and performance errors help to change parameters or structures. CPS theory goes further, introducing computer intelligence directly into physical objects. This creates a closed-loop system in which the digital version must be changed at the same time as the physical version to maintain accuracy.

Digital twins are an example of how to use CPS in engineering. Digital twins keep a very accurate virtual copy, get data from sensors in real time, simulate and provide suggestions for improving physical objects. For example, twins have been measuring vibration, temperature and pressure for the health of aircraft engines. The continuous learning module updates the degradation model to show the changes of wear and original data. Compared with the fixed method, this closed-loop mirror can reduce the prediction error by about 30% to 40%, and can carry out maintenance planning before failure [2].

Information theory gives us a mathematical reason to update only when necessary. This indicator measures our uncertainty about the status from the sensor. Mutual information indicates the importance of new observations to model parameters. When the change of distribution makes the predicted value increase above a critical value, targeted knowledge can be added and waste of calculation can be avoided. This view holds that continuous learning is not an unthinking retraining, but an information flow management, which reduces the amount of information in CPS architecture [3].

A new idea is to put the sensor based on information theory into the feedback hierarchy of CPS: the mutual information between physical measurement and model probability is used to trigger local update, so as to keep it simple and related to physical reality. These mechanisms make the system stable even when the situation changes, and link theory with engineering practice.

## 3. METHODOLOGICAL FRAMEWORKS AND KEY TECHNOLOGIES FOR CONTINUOUS LEARNING AND KNOWLEDGE UPDATING

An efficient framework combines distributed change detection with controlled adaptive mechanism; Concept drift detection algorithm monitors the statistical properties of data streams. When they see that the relationship between features and goals has changed, they will make targeted updates instead of retraining everything. Continuous learning based on regularization will punish the deviation from the weight of previous learning, and the replay experience will replay old samples from time to time to better retain knowledge. Dynamic architecture increases or decreases network capacity according to the novelty of tasks.

Reinforcement learning (RL) provides a good way to adapt to decision-making in a changing environment. In semiconductor factories, wafer manufacturing steps must adapt to available tools, performance changes and priority orders, and deep RL agents learn planning rules through simulation or actual production lines. The continuous learning version uses elastic weight integration or progressive neural network to add new planning constraints (such as those caused by supply problems), without forgetting the optimization skills already learned, and can maintain a performance improvement of 15% to 25% even if the situation changes [4].

Computer vision enhanced by incremental learning helps to check the quality online. In automobile painting line, convolutional network first learns from normal defects, but later sees new problems due to materials or time. By replaying the buffer or knowledge evaporation, the system can learn these new defects without forgetting the old ones, and can find more than 92% defects when using the edge without being too slow.

Edge computing is very important for updating knowledge in real time. By performing lightweight calculations and adjusting models on small machines close to objects, edge nodes avoid delays and data problems when using the cloud. With the hybrid system of edge cloud, the edge devices can deal with small changes immediately, and the cloud is updated from time to time [5].

These technologies are embodied in the digital twin framework that manages data, model evolution and operation. They help the system run well for a long time, but each method has advantages and disadvantages between adaptation and stability, which we will see later.

## 4. APPLICATIONS IN INTELLIGENT ENGINEERING SYSTEMS

The application of intelligent engineering shows how the progress of theory and method becomes useful in real life. In wind power generation, the digital twins of turbine gearbox use vibration and SCADA data and continuous learning module. When the gearbox rotates for a long time, the bearing wear will change; The gradual updating of the anomaly detection model triggered by the concept drift detector keeps the false alarm rate below 5% and helps to predict the remaining life several weeks in advance. Edge deployment allows vibration-based stop commands in less than a second, demonstrating how CPS feedback, information theory triggering and continuous learning work together [6].

Intelligent transportation system is another example. In order to control traffic lights and detect urban events, more and more people use computer vision pipeline to analyze camera images of intersections. Changes in traffic-due to work, weather or new habits after an epidemic-create the concept of drift, making the fixed model not so good. Visual models of edge deployment with online adaptive mechanism will be recalibrated for new flows, and they improve event detection by 18% to 22% compared with static models. The reinforcement learning layer also helps to optimize the flame when drift is detected, thus closing the CPS cycle between perception, decision-making and physical action [7].

In both areas, we have benefits, such as improving system availability, making better use of resources, and spending less money by taking preventive measures afterwards rather than reacting after problems occur. However, the closed-loop integration to increase profits may also spread errors: the wrong update of the model in the circulating system may generate congestion waves, and the wrong setting of the turbine model may lead to unnecessary downtime, or worse, miss major failures. These things prompt us to observe the border carefully.

## 5. CHALLENGES, LIMITATIONS, AND FUTURE PROSPECTS

Even if we see the prospect, continuous learning systems have great problems, which can alleviate our enthusiasm for uncontrolled use of them. Disaster entanglement is still a problem in neural architecture; Even advanced strategies, such as regularization and replay, still display errors when the task sequence is long or very different. In safety-critical CPS, such as autonomous inspection unmanned aerial vehicle (UAV) used to monitor bridges or pipelines, it is an unacceptable risk to accidentally remove the identification update of rare but catastrophic structural anomalies.

Frequently updated calculations and energy costs make the edge equipment with little heat capacity and energy tired. Each adaptation cycle uses memory and processing cycles that compete with the main reasoning tasks, which may lead to real-time delay. In addition, the ever-changing model is opaque, which makes verification and authentication difficult. The rules of safety-critical systems usually assume static and verifiable things, rather than ever-changing decisions.

Data privacy and security vulnerabilities become more serious when the system is frequently updated. Using joint learning or edge learning, you don't need to concentrate all the data in one place, but the local model may be attacked by poisoning attacks, which may spread false knowledge throughout the CPS network [8].

A new idea is to define "bounded adaptation" as protection based on system theory: combining information drift measurement with Lyapunov's closed-loop CPS stability analysis, only when they improve performance and are not far from the verified safe operation area can they be updated. This hybrid method improves the existing CPS theory and provides a logical method to find a balance between exploring new knowledge and using known knowledge.

In the future, we can use basic models trained on large engineering databases, neuromorphological hardware optimized for lifelong learning, and standard protocols of digital twin reference architecture for continuous learning.

## 6. CONCLUSION

The framework of continuous learning and knowledge updating is a very important tool for AI in intelligent and dynamic engineering systems. Using the new idea of uncertainty management based on system engineering feedback principle, CPS integration rules and information theory, these frameworks have achieved measurable benefits in adaptability, efficiency and flexibility in manufacturing and infrastructure fields. Practical examples of using digital twins, reinforcement learning, computer vision and edge computing show that this is possible in practice, but they also say that we must be very careful to avoid instability and the spread of errors.

The proper balance between benefits and limitations shows that if adaptation is not controlled, it will bring as much risk as its benefits. The proposed updating mechanism is driven and restricted by stability, which provides a way to solve these tensions. Future research must give priority to the realization of verifiability, resource sensitivity and privacy protection, so that the development of artificial intelligence can meet the needs of engineering system life cycle. Only through this good integration can continuous learning realize its transformative potential in intelligent engineering through AI.

## REFERENCES


[1] Parisi GI, Kemker R, Part JL, Kanan C, Wermter S. Continual lifelong learning with neural networks: A review. Neural Networks. 2019; 113:54-71. https://doi.org/10.1016/j.neunet.2019.01.012

[2] Tao F, Cheng J, Qi Q, Zhang M, Zhang H, Sui F. Digital twin-driven product design, manufacturing and service with big data. International Journal of Advanced Manufacturing Technology. 2018; 94:3563-3576. https://doi.org/10.1007/s00170-017-0233-1

[3] Lu Y, Liu C, Wang KI, Huang H, Xu X. Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing. 2020; 61:101837. https://doi.org/10.1016/j.rcim.2019.101837

[4] Cheng J, Zhang H, Tao F, Juang CF. DT-II: Digital twin enhanced Industrial Internet reference framework towards smart manufacturing. Robotics and Computer-Integrated Manufacturing. 2020; 62:101881. https://doi.org/10.1016/j.rcim.2019.101881

[5] Zhou Z, Chen X, Li E, Zeng L, Luo K, Zhang J. Edge intelligence: Paving the last mile of artificial intelligence with edge computing. Proceedings of the IEEE. 2019;107(8):1738-1762. https://doi.org/10.1109/JPROC.2019.2918951

[6] Jourdan N, et al. Handling concept drift in deep learning applications for manufacturing. Procedia CIRP. 2023; 118:234-239. https://doi.org/10.1016/j.procir.2023.06.039

[7] Zhang CY, Xu WJ, Liu JY, Liu ZH, Zhou ZD, Pham DT. Digital twin-enabled reconfigurable modeling for smart manufacturing systems. International Journal of Computer Integrated Manufacturing. 2021;34(7):709-733. https://doi.org/10.1080/0951192X.2021.1919321

[8] García Á, et al. Towards a connected Digital Twin Learning Ecosystem in smart manufacturing. Computers & Industrial Engineering. 2022; 172:108567. https://doi.org/10.1016/j.cie.2022.108567