Some Practice of Intelligent Manufacturing

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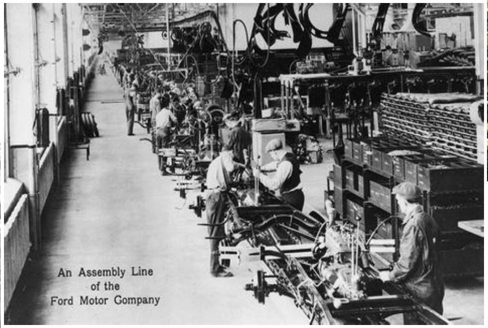
Contents

Industry Evolutions

Industry 4.0
"Data"

Industry 3.0
"Information"

Industry 2.0
"Electricity"



Industry 1.0
"Goal"

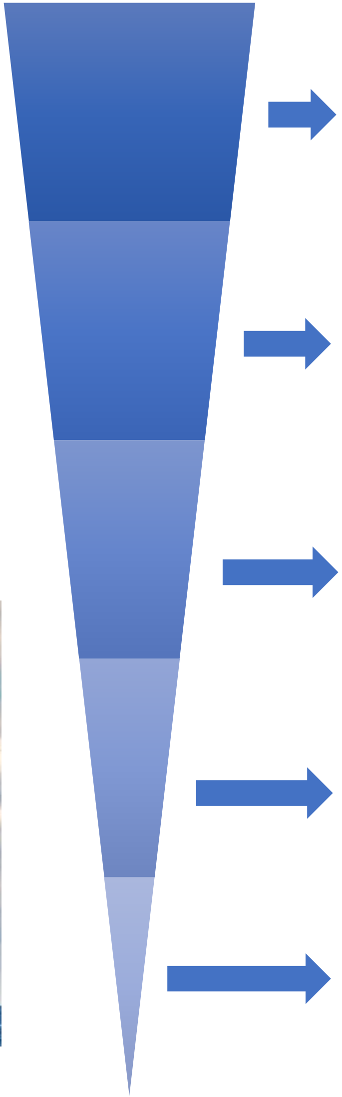
CLOUD + IOT

Today

Unexplored Value in Data

Things generate more data every day	
1 PB	Mining
480 TB	Jet engine
24 TB	Automated manufacturing
1 TB	Large refinery
0.8 TB	Large retail shop
0.5 TB	US smart meters

30000 sensors on an offshore oil rig



Data acquisition, about **40%** of the data has never been saved.

Data management, most data can not be monitored in real time.

Data analysis, limited to few indicators.

Data deployment, analysis results cannot be used directly.

1% of data is used for business decisions

--Mckinsey

Industrial Internet for Intelligent Manufacturing

Tools (Data Science)

Artificial intelligence

+

Big data analytics

+

Cloud computing

+

Internet of things

Industrial Internet Platform

Demands (Manufacturing)

New methods

- Improving efficiency, quality and value

+

New solutions

- Digitalization, intelligence
- Products, production

+

New eco-system

- Data-driven, software defined
- Platform, collaboration

Industrial Internet for Intelligent Manufacturing

Machine tools

Automobile

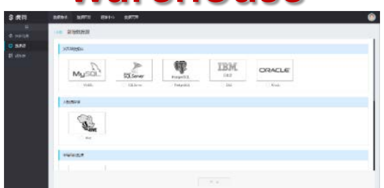
Aircraft

Chemical industry

Manufacturing

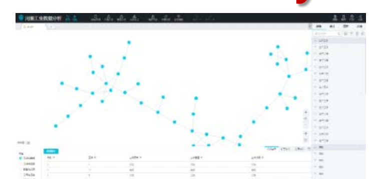
construction

Industrial data warehouse

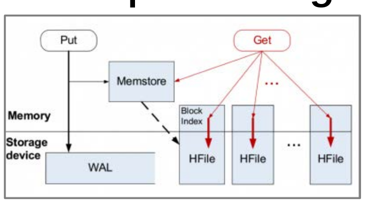


Intelligent APPs development platform

Complex data networks analysis



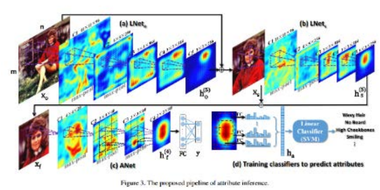
Time-series & image data processing



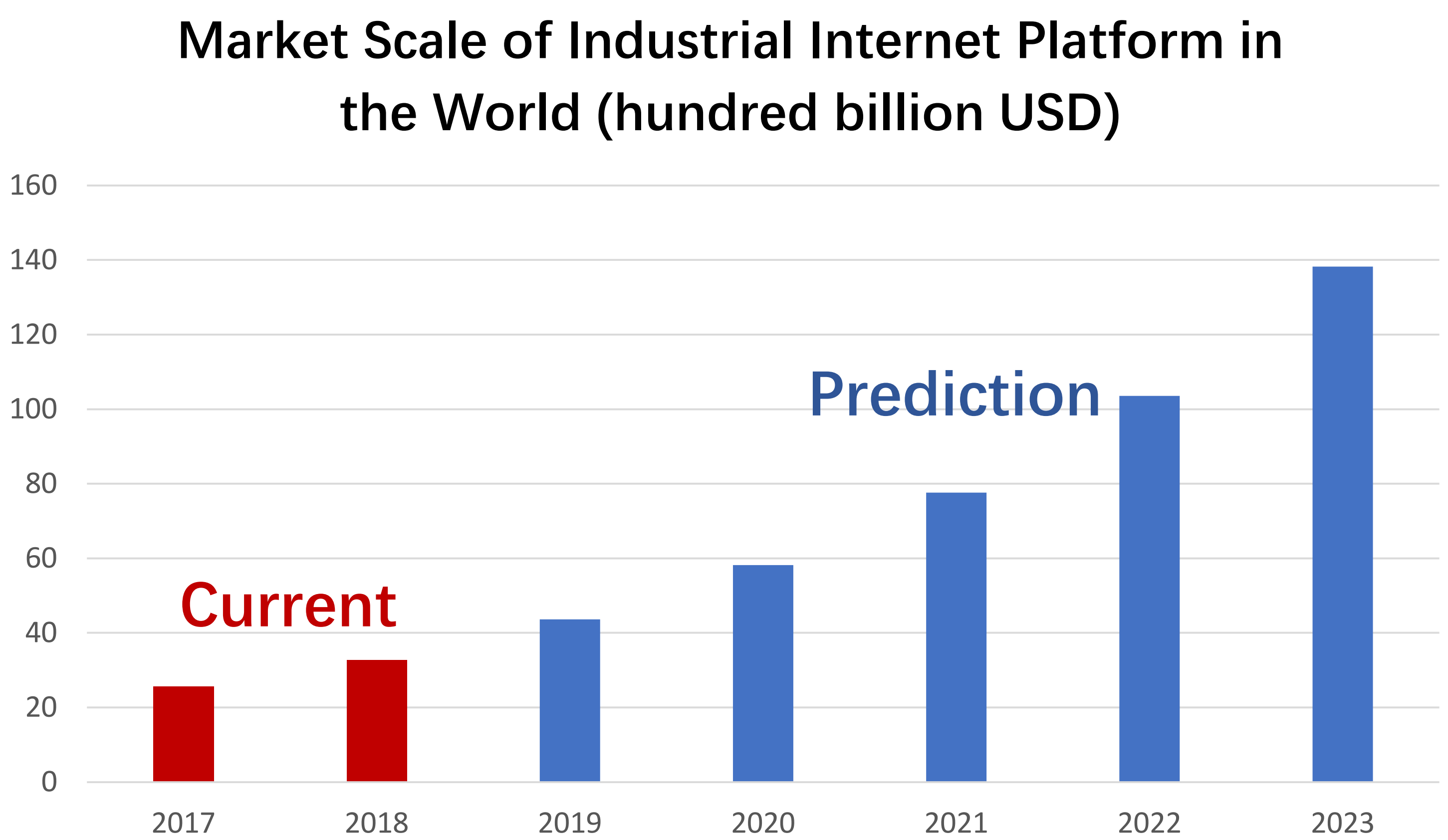
Operational

AR/VR/Rendering

Edge computing



Industrial Internet Market



America, Europe and **Asia** are the most active markets of Industrial Internet

Source： MarketsandMarkets

Industrial Internet Applications

Use cases

Product-as-a-service

- Predictive anomaly detection
- Digital Twins
- Guided service workflow
- Upsell and cross sell
- Smart MRO
- Predictive maintenance

Factory of the future

- Factory assistance
- Automatic part sorting
- Smart systems
- Product traceability
- Task Scheduling
- Process optimization
- AGVs & Robots
- Health and safety

Intelligent supply chain

- Sourcing & procurement
- Supply chain management
- Inventory planning
- Integrated business management
- Demand forecasting
- Integrated track and trace
- Predictive quality, yield
- Warehouse automation

Contents

Case 1: Assembly Process Monitoring

Background：

- CFMOTOR is one of the largest motorcycle manufacturers in China
- Low-volume multi-variety engine production
- Highly relying on humans for engine assembly
- High risk of incorrect assembly operations
- Assembly sequence must be abided by to ensure quality

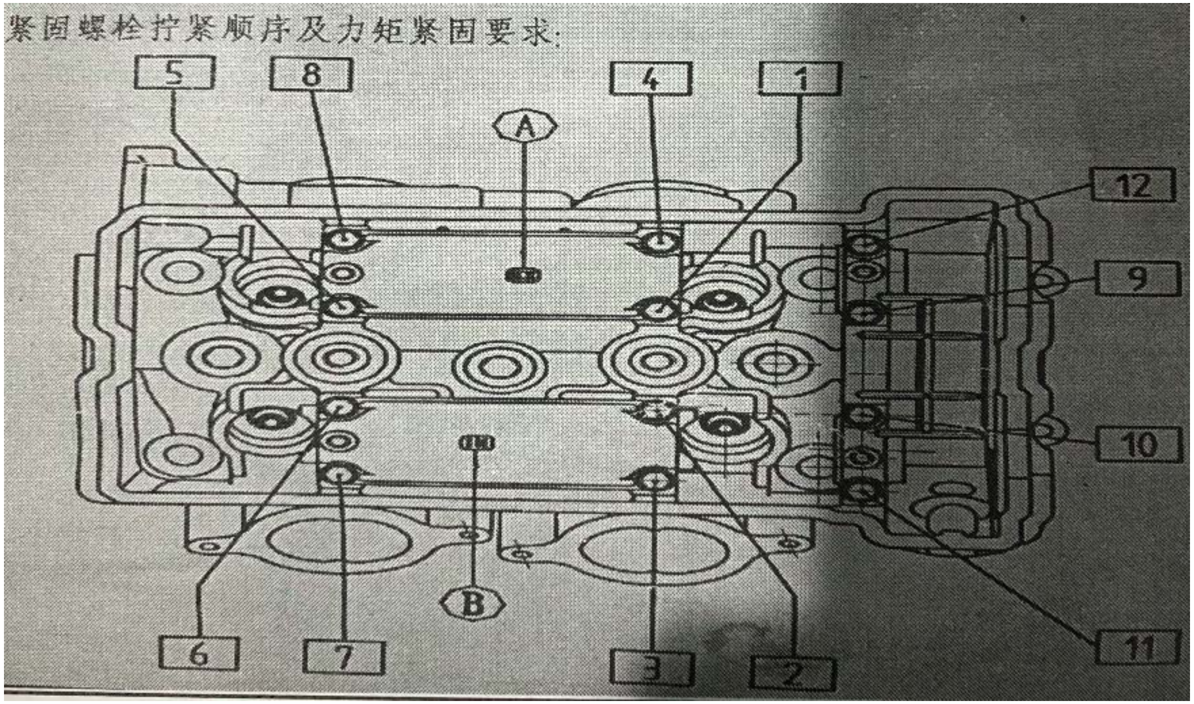
How to prevent assembly errors with minimum change and investment on the production line?

Case 1: Assembly Process Monitoring

Old situation:

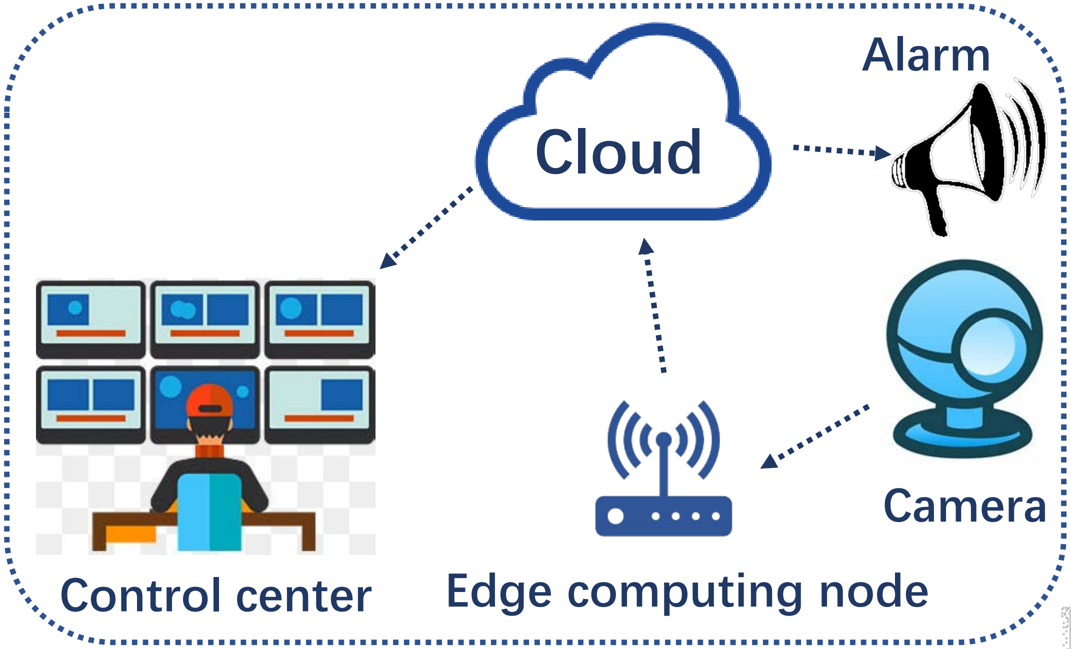
- Periodic inspection tours by the managers
- Can only check for a short time for each assembly spot

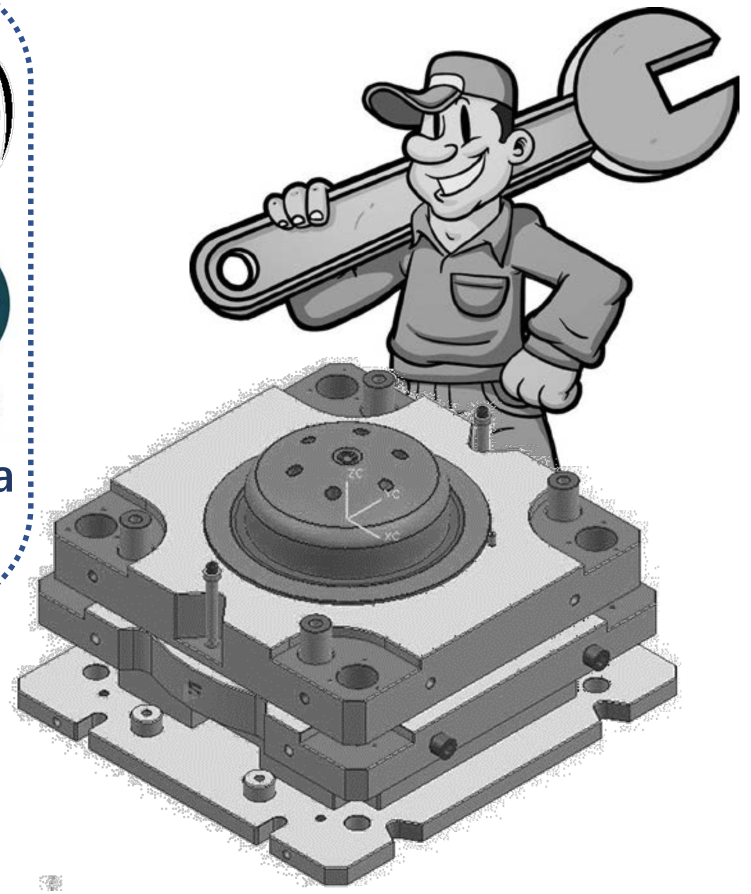
Using AI techniques, the sequence can be checked with streaming images in real time



Standard assembly sequence

Case 1: Assembly Process Monitoring





Assembly spot

Benefits：

- Low cost, no need to change current workflow
- Can quickly implemented to all the spots
- Using cloud edge computing for fast response
- Reducing managers’ workload

Case 1: Assembly Process Monitoring

Staple object detection algorithm

- Edge features
- Insensitive to light conditions
- Sensitive to deformation

HOG Feature

Histogram

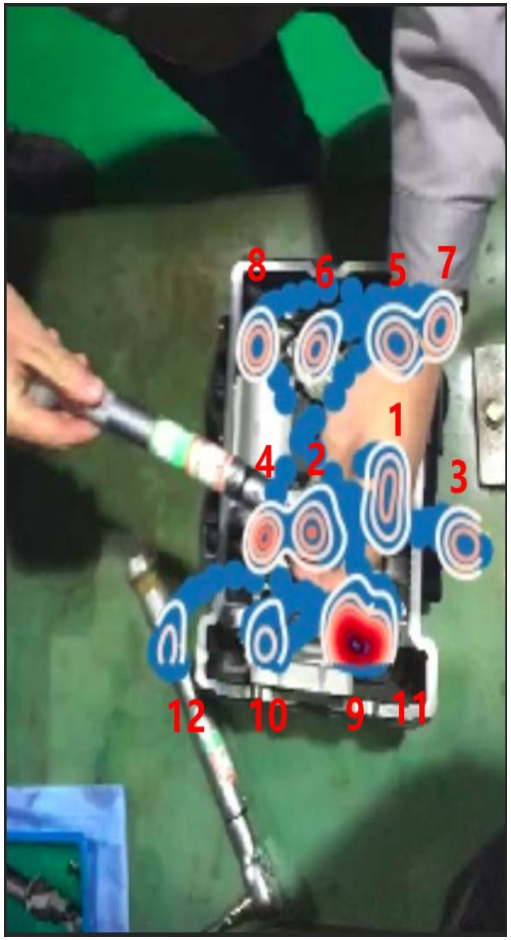
Object location

- Color features
- Sensitive to light conditions
- Insensitive to deformation

Bertinetto, Luca, Jack Valmadre, Stuart Golodetz, Ondrej Miksik, and Philip Torr. 2016. “Staple: Complementary Learners for Real-Time Tracking.” In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1401–1409. doi:10.1109/CVPR.2016.156.

Case 1: Assembly Process Monitoring

Hand tracking



Sequence identification

Results:

- Marking assembly trajectory using machine vision
- Comparing the sequence with standard requirements

Next step:

- Integrating torque signals for comprehensive quality monitoring

Case 1: Assembly Process Monitoring

Benefits of the proposed method：

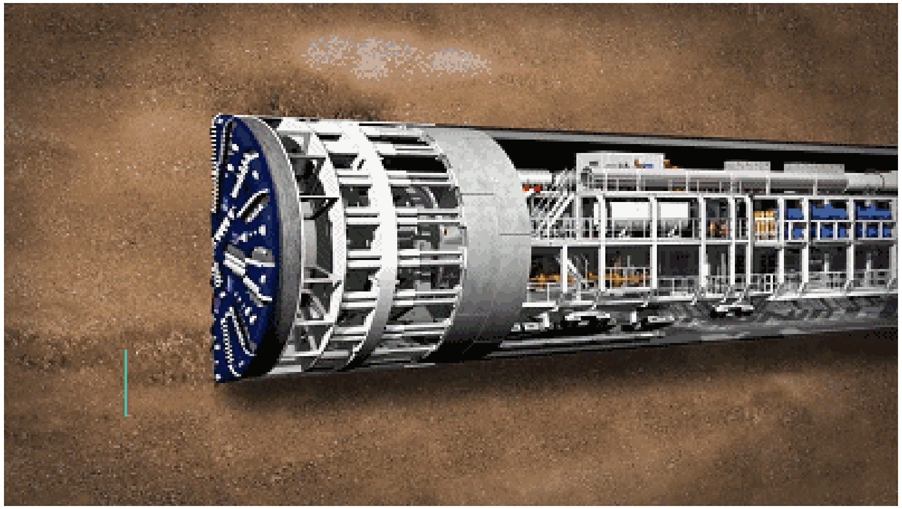
- **Minimum changes and investment** to the production line to achieve assembly quality monitoring and control
- **Real-time monitoring and alarming** when errors occur to improve the product quality
- Can be **easily generalized** to other similar assembly lines

Case 2: Automatic TBM Driving

Background:

- China Railway Construction Heavy Industry Co., Ltd. is the largest tunnel boring machine (TBM) manufacturer
- TBM is highly expensive so its **life expectation matters**
- Dynamically adjusting boring parameters can prolong its life
- Mainly relying on **drivers' experience** to select optimal settings
- High cost and time consumption on training
- Human may not be as stable and focused all the time

Can we teach a system to drive TBM efficiently and robustly?



Case 2: Automatic TBM Driving

Main challenges:

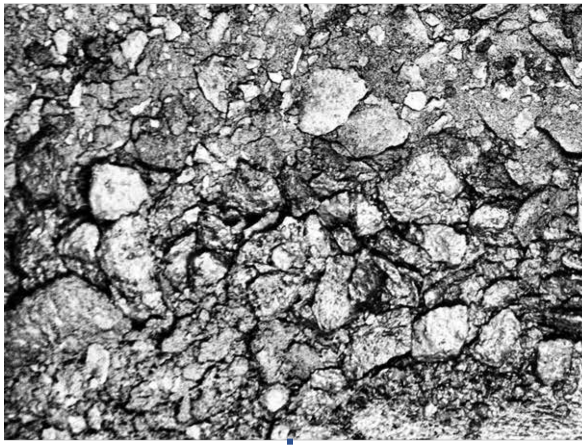
- Environment sensing
- TBM key parameters monitoring and analysis
- Automatic driving with real-time information (future work)

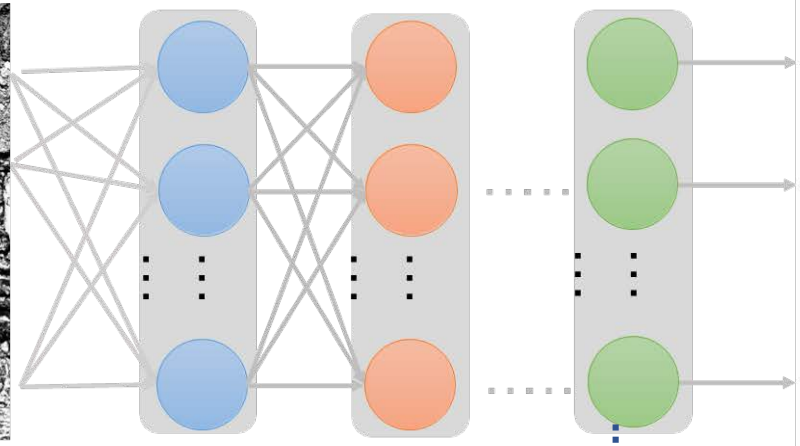
name	score
主驱动1号电机扭矩_平均_趋势	0.0393092
刀盘功率_平均_趋势	0.0386799
主驱动1号电机输出功率_平均_趋势	0.0326572
主驱动4号电机输出功率_平均_趋势	0.0292374
主驱动6号电机输出功率_平均_趋势	0.0271268
主驱动1号电机扭矩_标准差_趋势	0.0208778
刀盘功率_最大_趋势	0.0193167
主驱动9号电机扭矩_平均_趋势	0.0191646
刀盘扭矩_平均_趋势	0.0189305
主驱动10号电机电流_平均_趋势	0.0164758
主驱动4号电机扭矩_平均_趋势	0.0163336
主驱动10号电机扭矩_平均_趋势	0.015664
刀盘扭矩_最大_趋势	0.0153605
主驱动4号电机输出功率_最大_趋势	0.0152369
主驱动1号电机输出功率_最大_趋势	0.0152247
右拖拉油缸压力_平均_趋势	0.0151717
主驱动10号电机输出功率_平均_趋势	0.0151262
主驱动10号电机扭矩_标准差_趋势	0.0149131
主驱动1号电机电流_平均_趋势	0.0135083
主驱动6号电机扭矩_平均_趋势	0.012932
主驱动4号电机电流_平均_趋势	0.0128255
主驱动5号电机扭矩_平均_趋势	0.012773
主驱动9号电机输出功率_平均_趋势	0.012662

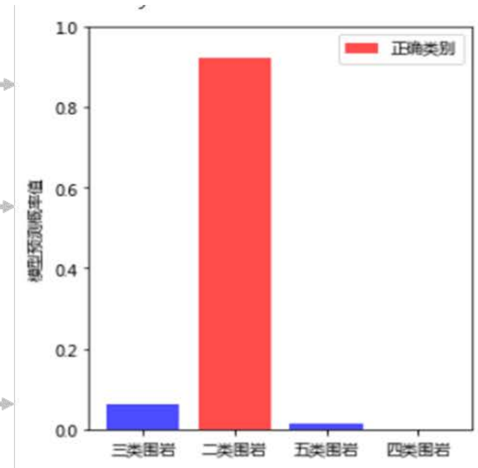
Hundreds of operating parameters

Case 2: Automatic TBM Driving

Environment Sensing: Rock type classification







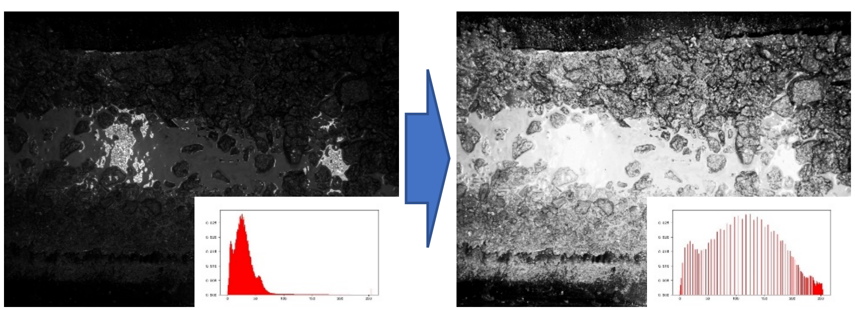
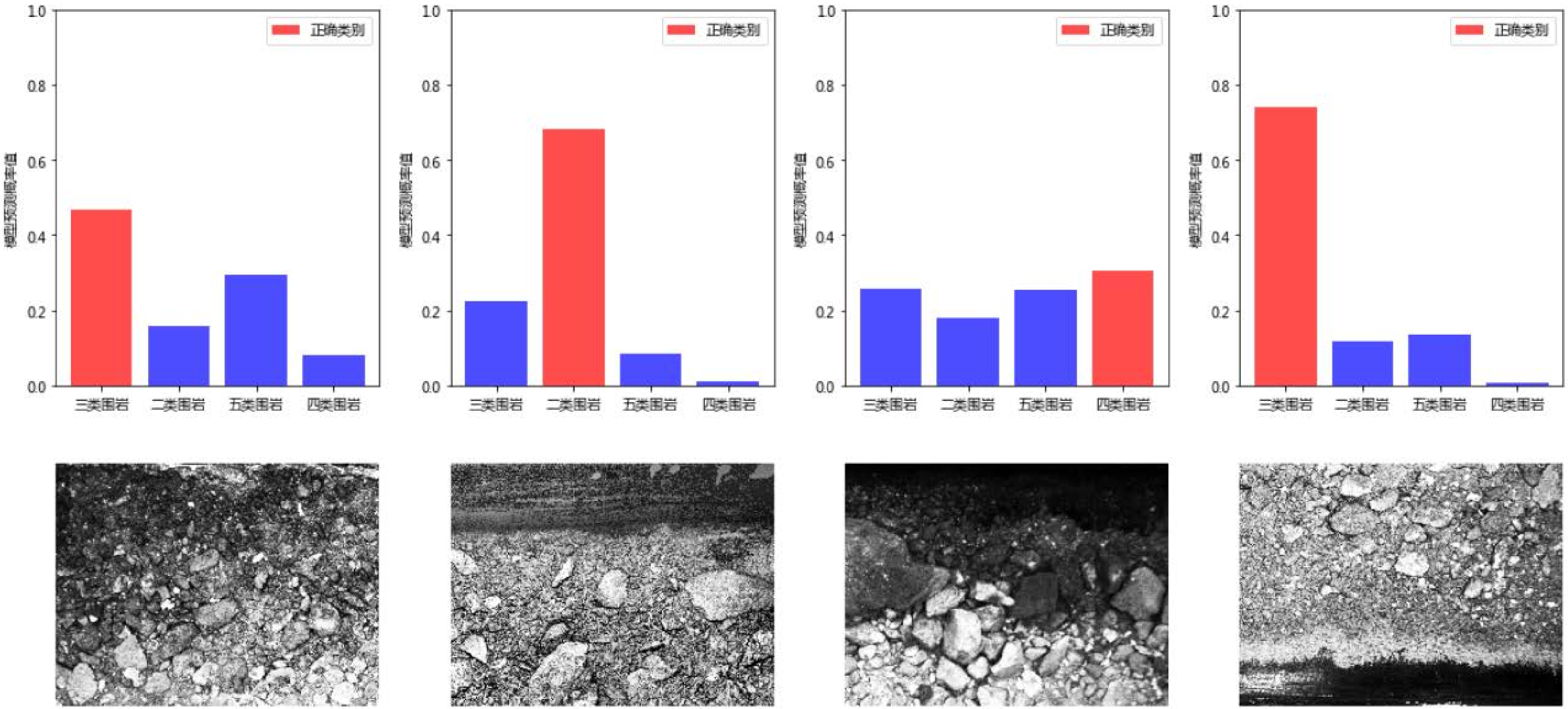


Image preprocessing： Using histogram equalization to increase contrast of the image and highlight the rock edges.

CNNs： according to the comparison of different networks, VGG16 performs the best and can quickly achieve the similar level of human classification accuracy.

Case 2: Automatic TBM Driving

Environment Sensing: Rock type classification

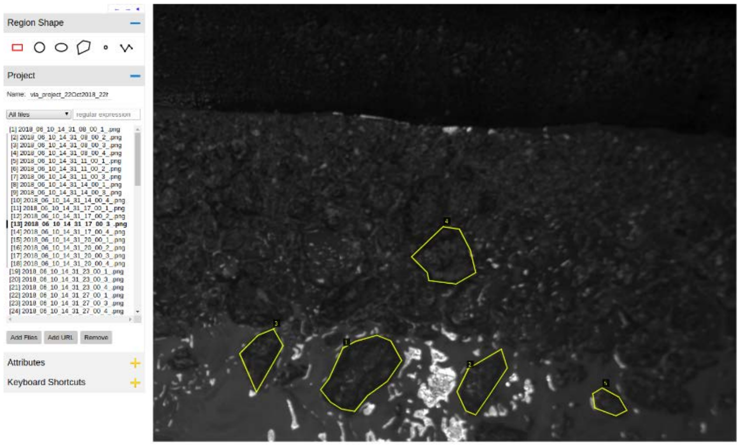


4 types of rocks classification results

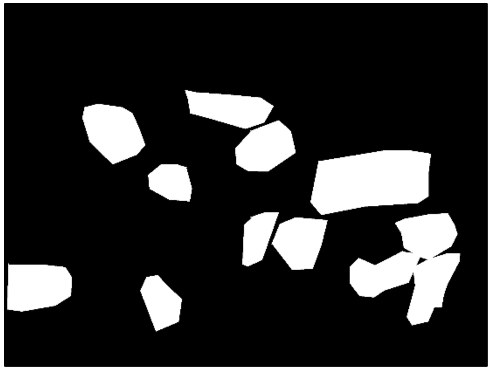
Case 2: Automatic TBM Driving

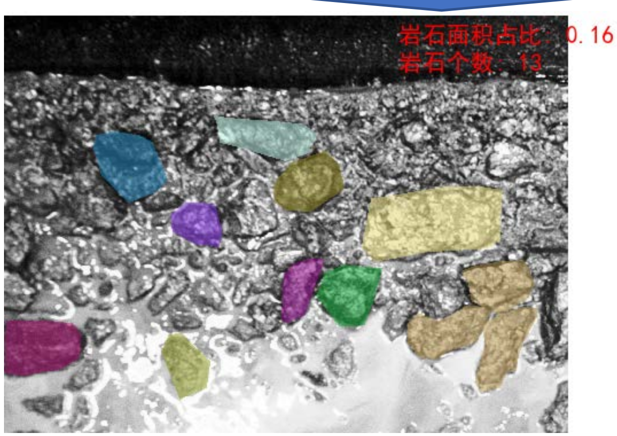
Environment Sensing: Rock size measurement

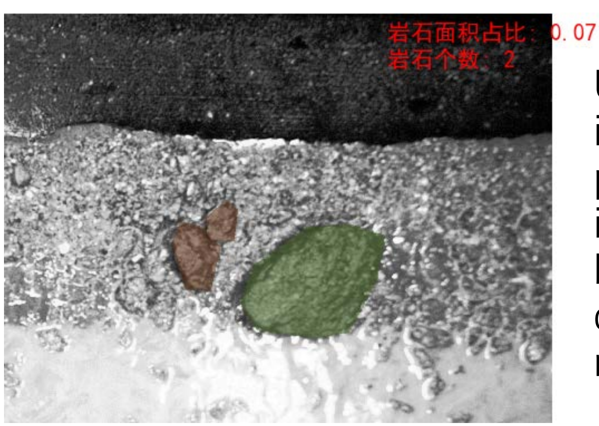
Labelling on the Xuelang OS platform, using 80 images for training and 16 for verification.



- Digging the statistics of rock distribution
- Simplify the drivers' tasks for environment evaluation
- One of the enabling technologies for self-driving TBM





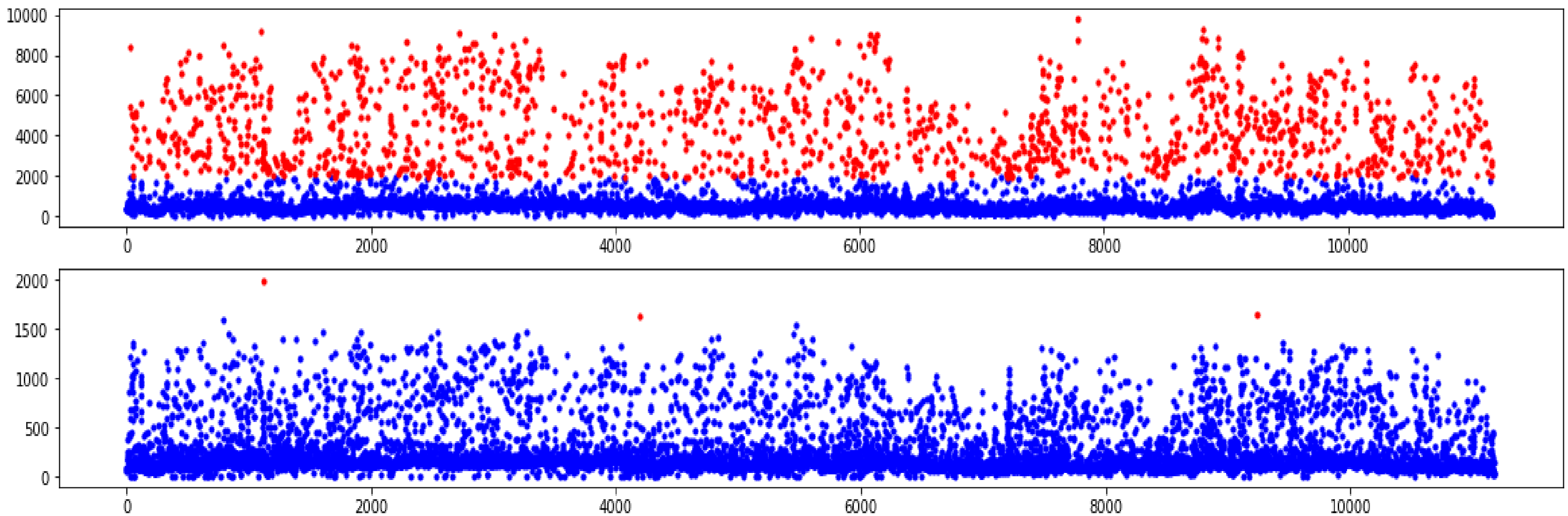


Use Unet Network for image segmentation on the pixel level. Divide the image as rock areas and background areas. Then, calculate the size and number of rocks.

Case 2: Automatic TBM Driving

Key parameters monitoring and analysis: cutter load analysis

Instable load causes the machine receiving different forces at different areas. As a result, the machine may **not be moving straight** as it supposes to be. The machine **life will be shortened** as well. Therefore, it is crucial to keep the load as stable as possible.



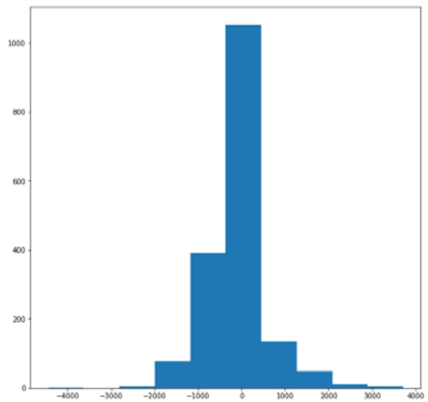
Load distribution for a driving period (Red dots are abnormal values)

Case 2: Automatic TBM Driving

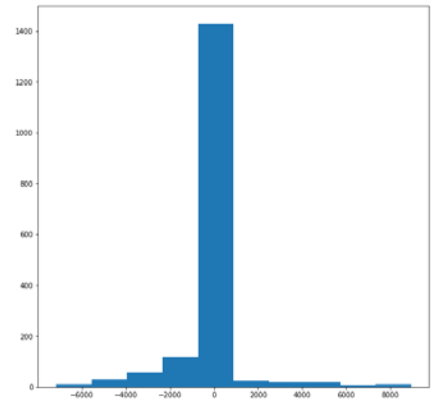
Key parameters monitoring and analysis: cutter load analysis

Examine the drivers' behaviors and their results when the load are out of boundary.

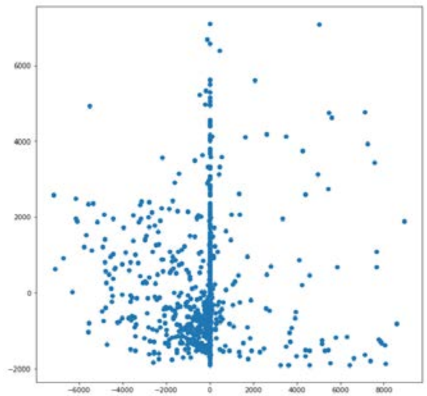
Cutter rotation speed settings



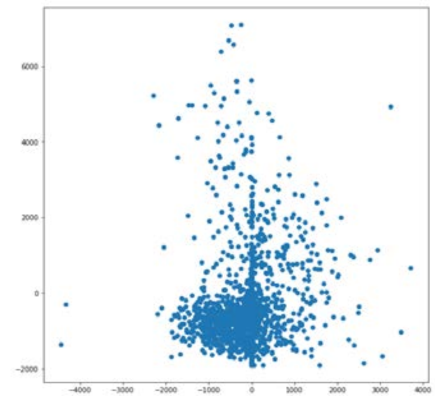
Cutter feeding speed settings



Cutter actual rotation speed



Cutter actual feeding speed



Findings: reducing the cutter rotation and feeding speeds can reduce the load variation

Case 2: Automatic TBM Driving

Benefits of the proposed method：

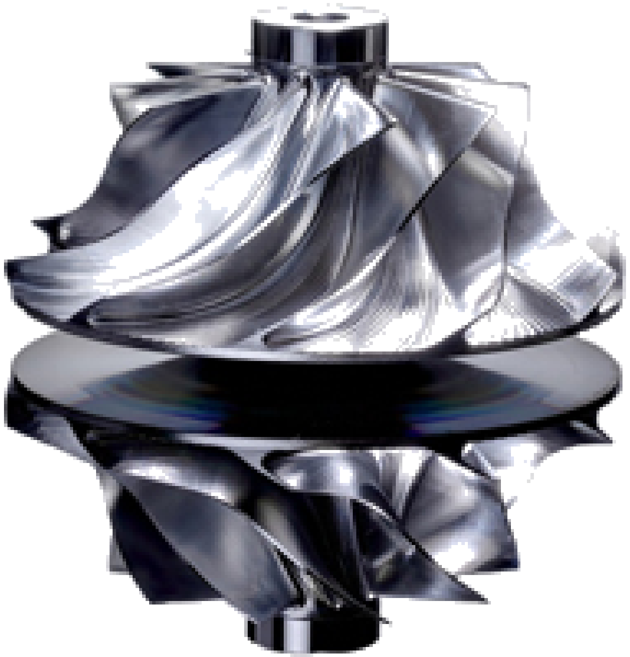
- Deep learning methods can **accurately recognize the type and size of rocks**, which can be used for automatic parameter adjustment
- Drivers' efficient driving skills can be extracted from the historical data
- These technologies provides the possibility **to automatically drive TBM** in a **more efficient and stable** manner

Case 3: Turbo Blade Surface Inspection

Background：

- Wuxi BEST is a Chinese automobile components manufacturer
- Providing turbo blades and other precision components
- Surface quality of turbo blades is critical
- Relying on humans for inspection, could be instable, high training cost and low scalability.
- Getting more difficult to recruit inspectors

How to automate the complex surface inspection process?



Case 3: Turbo Blade Surface Inspection

AI-enabled machine vision architecture

Application Layer
- Scratch
- dirt
- Intact barcode
- Intact edges
- Text error
- Bright spot
- Shape deformation

Management Layer
- Task management
- Model management
- Log monitoring
- Data management
- Mirror management

Computation Layer
- Feature mapping
- Deep learning
- Transfer learning
- Image segmentation
- Image classification
- Object tracking

Infrastructure Layer
- CPU
- GPU
- Edge computing node
- Distributed computing environment

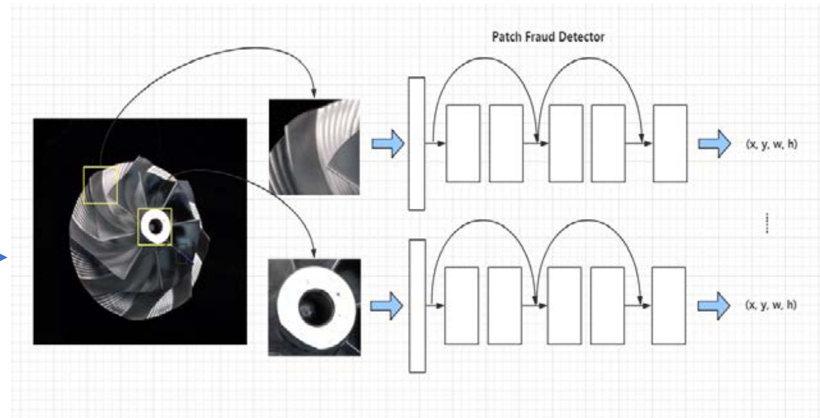
Case 3: Turbo Blade Surface Inspection

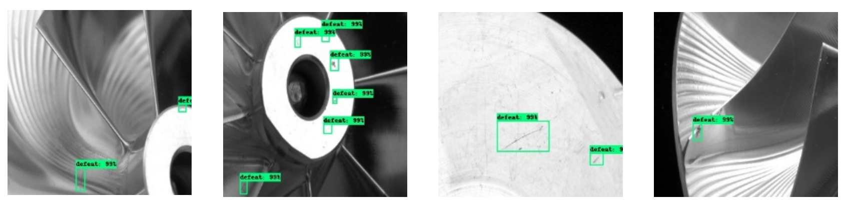
	Traditional machine vision	Deep learning
Feature extraction	Manually extracted, difficult for complex features	Automatically extracted, insensitive to feature complexity
Anti-interference	Need stable environment, sensitive to images' instability	Have tolerance to some degree of condition changes
Learning capability	Low	Can improve with accumulated data

Case 3: Turbo Blade Surface Inspection

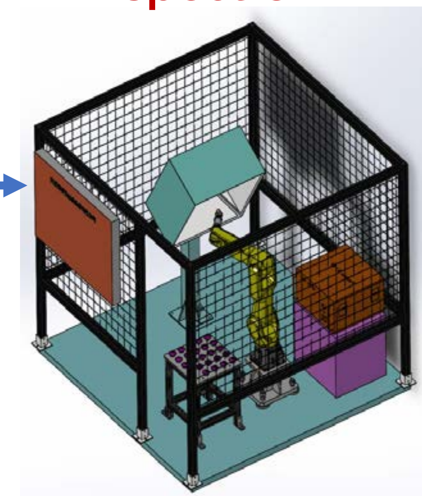
Shooting strategy design

Deep residual networks





Objective: fully automatic inspection



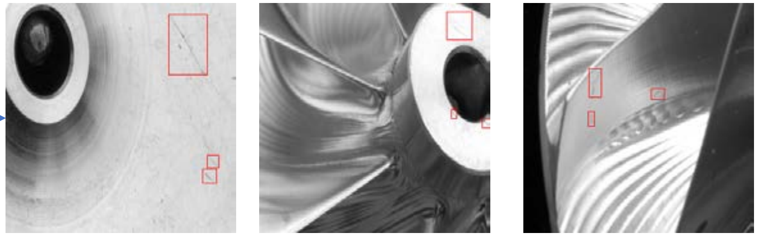
- All surfaces are covered
- High resolution camera

- Deep learning model, high flexibility and accuracy
- Image segmentation, high recall and precision rate

- Free up to 90 workers

Case 3: Turbo Blade Surface Inspection

Automatic image capturing



81 images in total, 156 **scratch defects**, 64 images (120 defects) for and 17 images (36 defects) for verification

	Results
Precision	85.51%
Recall	87.65%
mAP	87.04%

Case 3: Turbo Blade Surface Inspection

Benefits of the proposed method：

- Surface inspection is one the **most human-intensive** operations
- Deep learning models can assist or even replace human with this repetitive tasks
- Straightforward process and can achieve **near 90% accuracy**
- **High scalability**, can be quickly deployed to multiple inspection spots

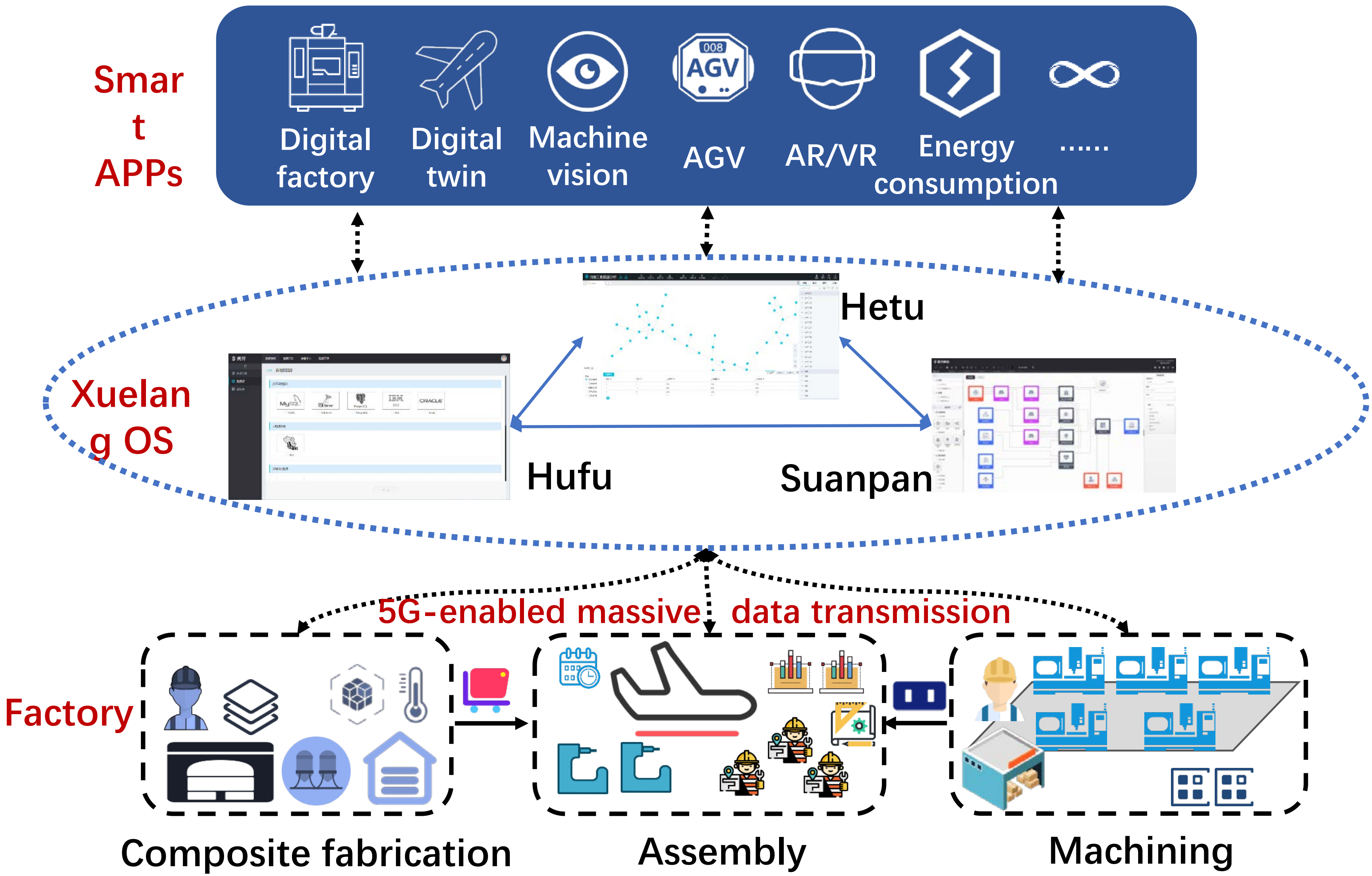
Case 4: Aircraft Manufacturing Brain

Background:

- COMAC is a Chinese commercial plane manufacturer
- Plane manufacturing process is extremely complex, with a huge amount of heterogeneous data
- A lot of management and operations are highly relying on human involvement
- Data are not well used

How to dig up the values in the manufacturing data and improve production efficiency?

Case 4: Aircraft Manufacturing Brain

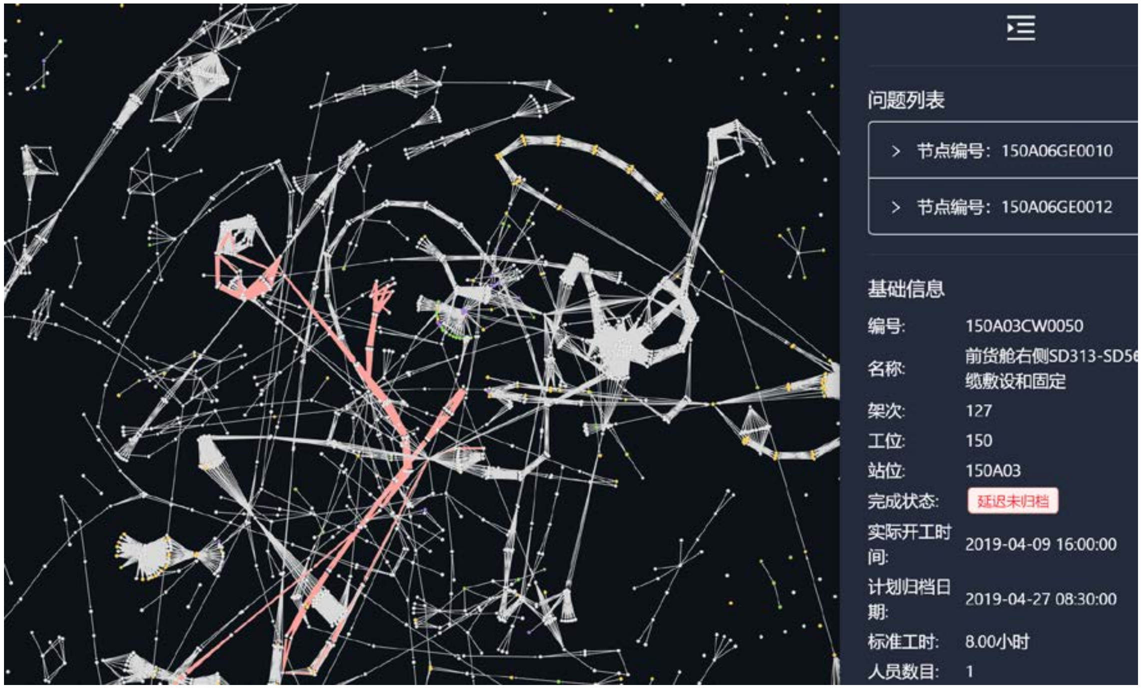


Case 4: Aircraft Manufacturing Brain

Virtual factory management platform

Case 4: Aircraft Manufacturing Brain

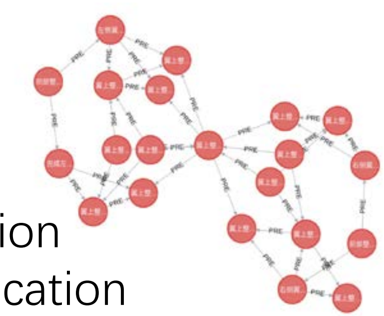
Complex assembly process modelling and optimization



6000+ nodes (AO), each AO has 30 assembly operations

- Redundant job discovery

- Key operation identification

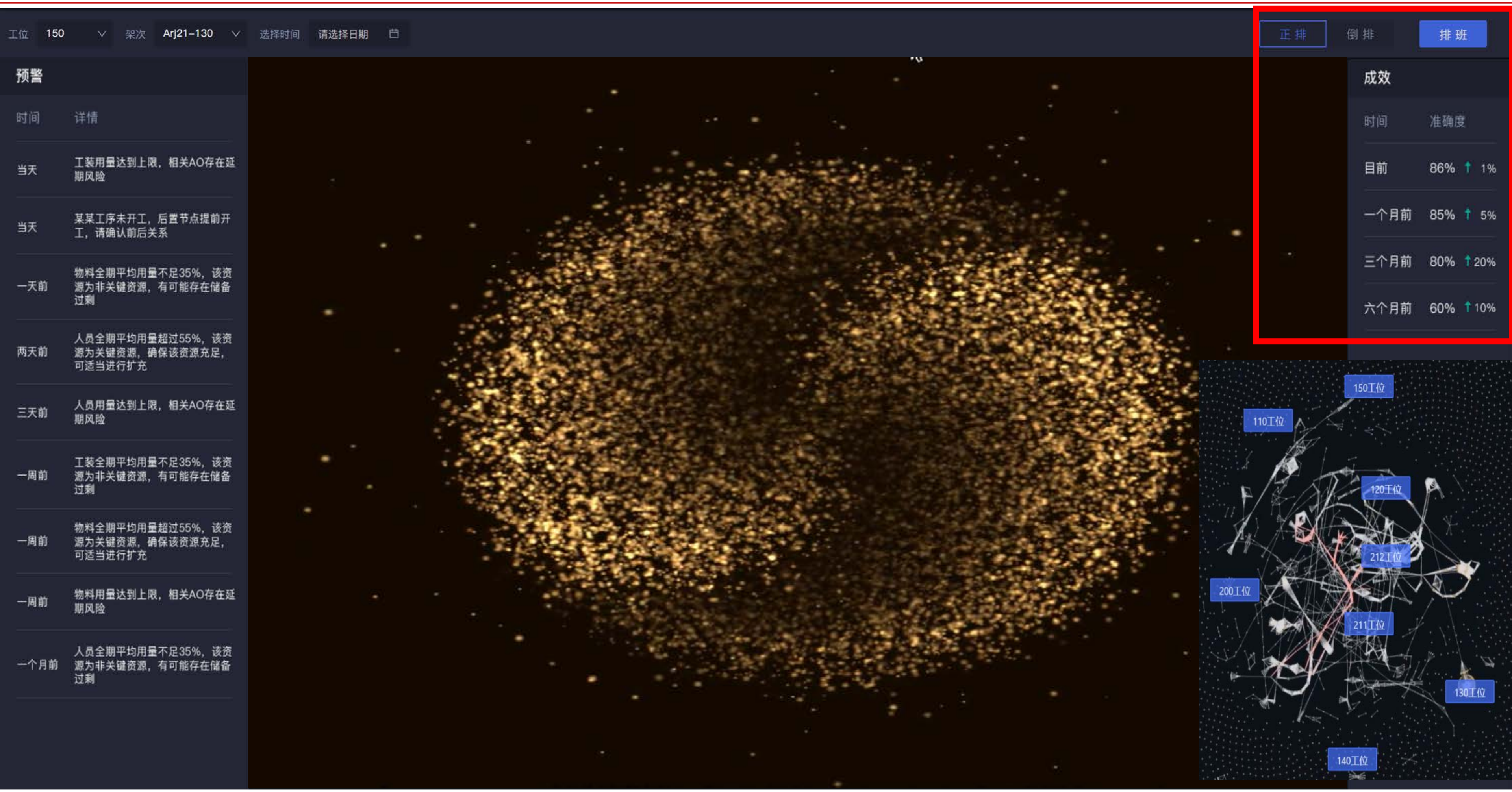


Traditional method:
divide huge problem to a body of smaller problems and assign people to separately deal with them

Method using complex networks:

- Global modelling & analysis
- Redundant job discovery
- Key operation identification
- Delay prediction
- Task scheduling optimization

Case 4: Aircraft Manufacturing Brain

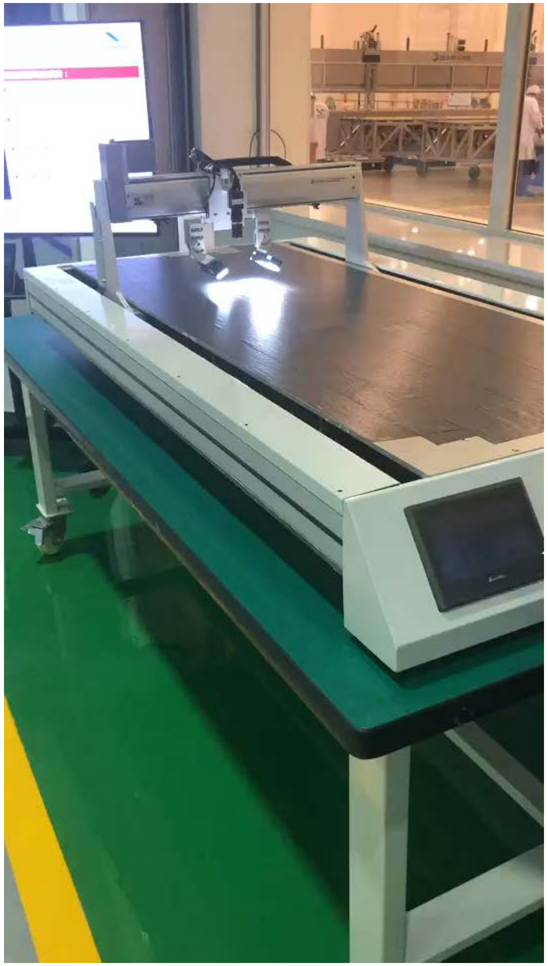


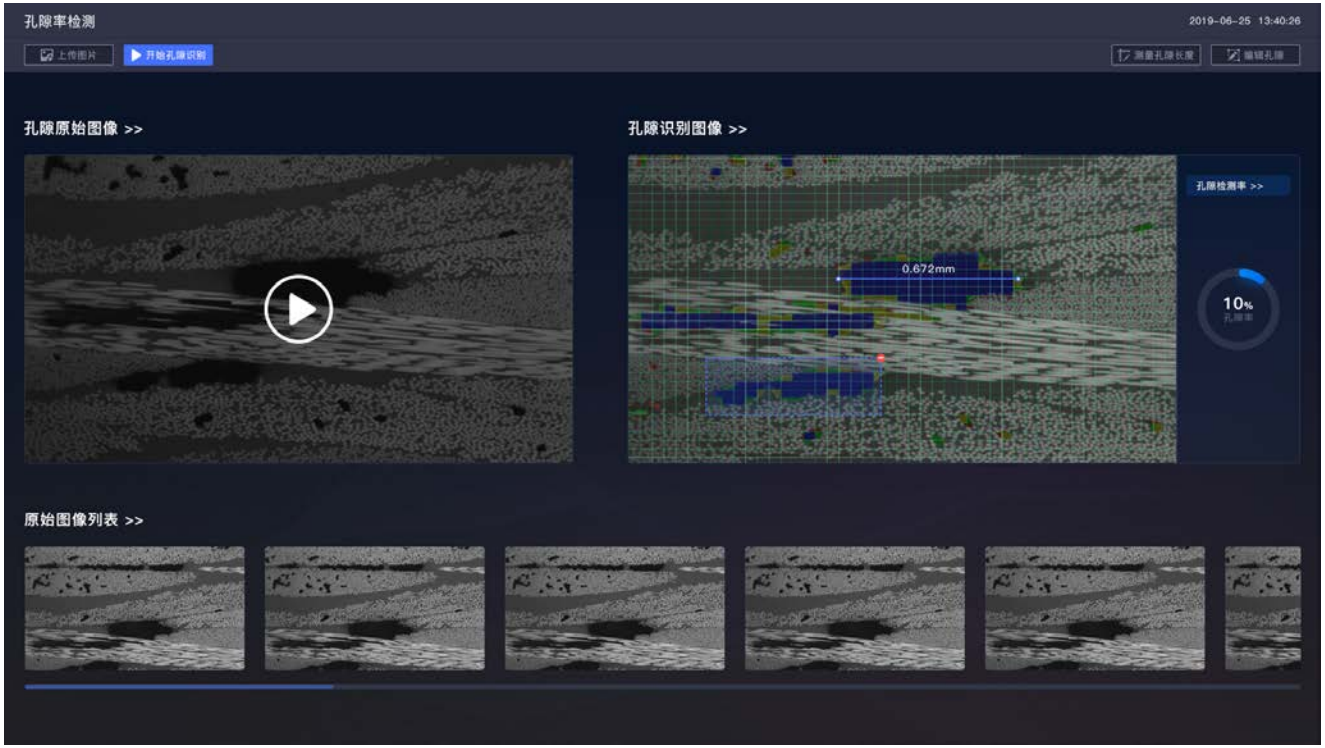
Manual task scheduling： low implementation accuracy, difficult to follow in practice

Task scheduling optimization： **implementation is increased from 60% to 80%**

Case 4: Aircraft Manufacturing Brain

Deep learning method for composite porous rate inspection





- Integrating cameras, lights, motion control units, etc.
- 5G-enabled real-time video data transmission
- Pixel level image segmentation for porous detection

Case 4: Aircraft Manufacturing Brain

Benefits of the proposed method：

- Digital factory twin enables managers to **efficiently monitor** the whole factory remotely in real time
- Complex networks-enabled assembly process modelling can provide **global analysis and optimization** capabilities
- 5G enables massive data to be transmitted in real time for **fast response**
- Deep learning methods can **automate the visual inspection processes**

Case 5: Industrial Internet for Bearing Production

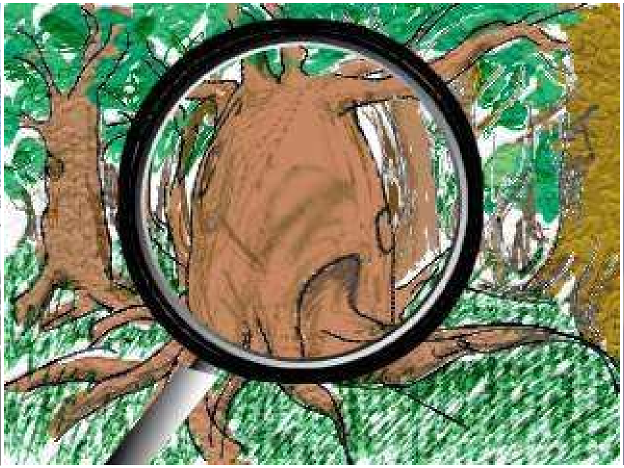
Background：

- HZF is one of the largest precision bearing manufacturers in China
- Highly automated production line
- Has many software such as MES, ERP, WMS, etc.
- Most of the data are not used

Case 5: Industrial Internet for Bearing Production

Issues for manufacturers with increasing size of data

Multi-system, multi-department	Lack global perspective	Unpredicted problems

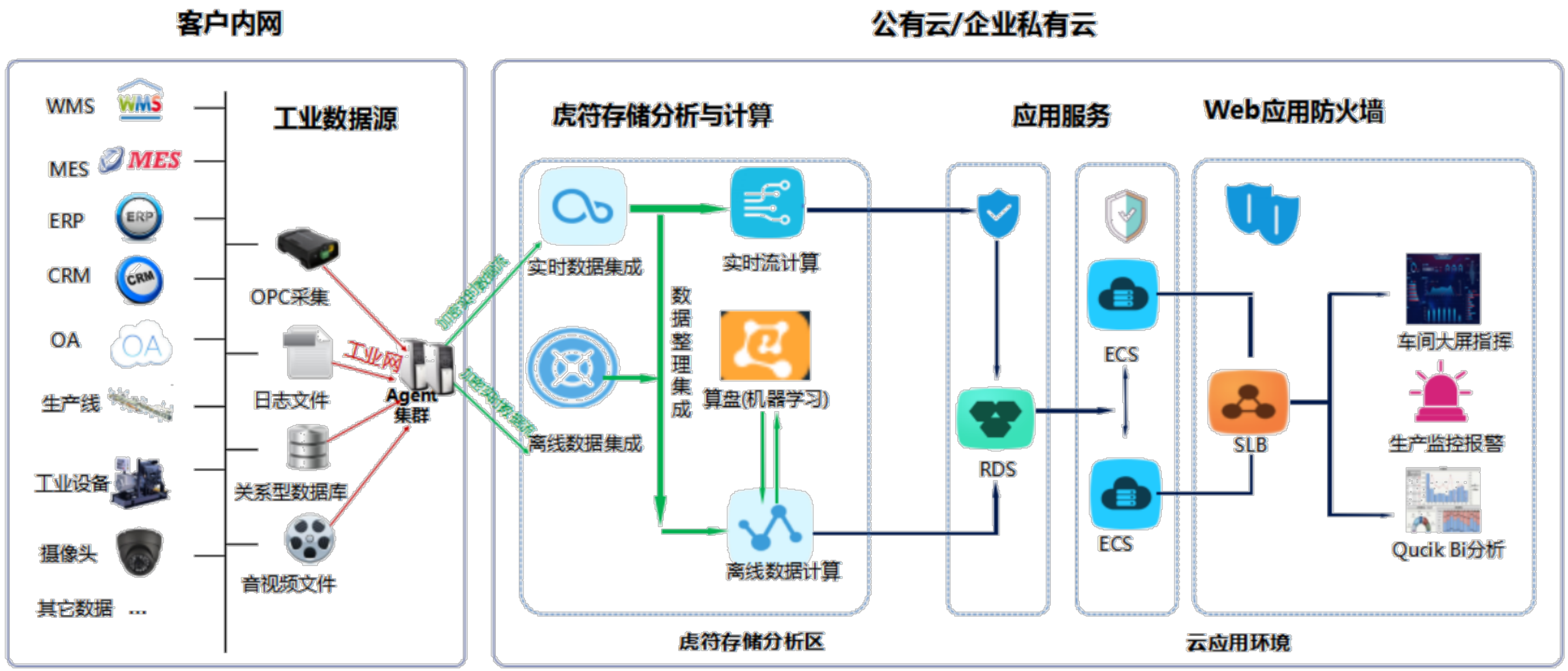


Heterogeneous data	Uninformed decisions	Inefficient operation & management

Developing industrial internet platform for bearing production

Case 5: Industrial Internet for Bearing Production

Data management system architecture



- ➢ integrating data from databases, machines and manual inputs
- ➢ Online data and offline data processing
- ➢ Public & private cloud deployment

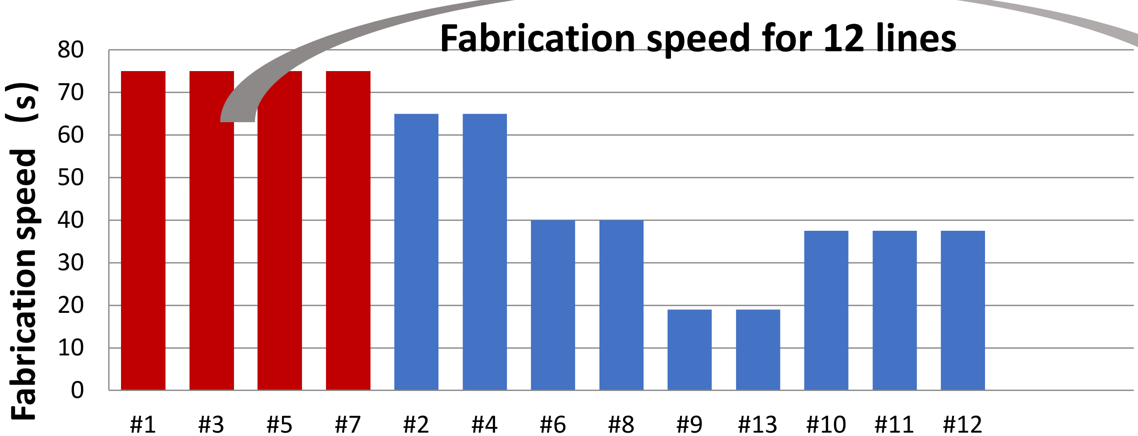
Case 5: Industrial Internet for Bearing Production

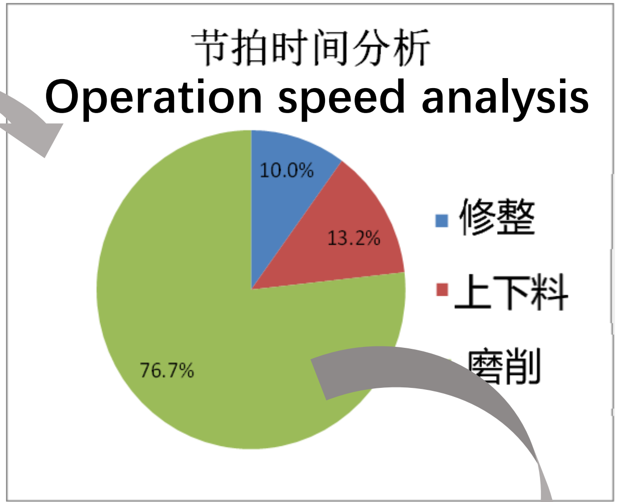
Enterprise monitoring board

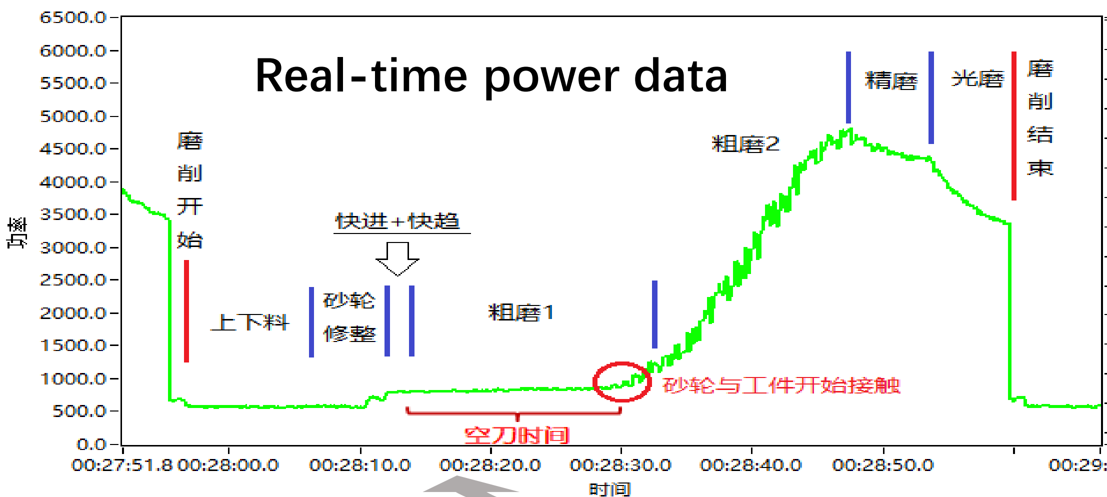
（点击图片进入在线版）

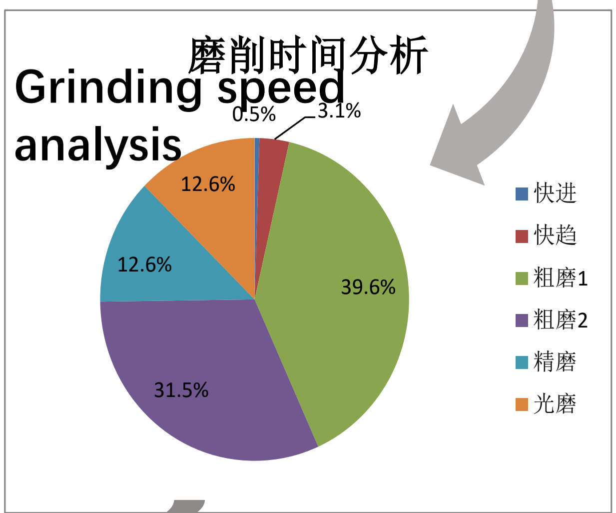
Case 5: Industrial Internet for Bearing Production

Example of data analytics: optimizing production efficiency









Case 5: Industrial Internet for Bearing Production

Findings:

- Non-grinding processes (i.e. grinding wheel maintenance and material loading) occupy 23.2% time.
- It takes 18.86s (39.6%) on rough grinding, while 15s of them are without loading.
- The grinding parameters have an obvious influence on the grinding efficiency.

	Solutions	Expected Results
1	Using acoustic monitoring system	Automatically identify remaining part geometry and reduce unloading time. This can reduce 7-13s of the rough grinding time.
2	Adjust grinding parameters	Optimize grinding parameters and improve grinding speed. This can reduce 3-5s of the grinding time.
3	Using better grinding wheel to reduce wheel maintenance time.	1、Using sharper wheel to improve grinding speed. This can reduce around 3s. 2、Using CBN wheel. This can reduce around 5s.

Case 5: Industrial Internet for Bearing Production

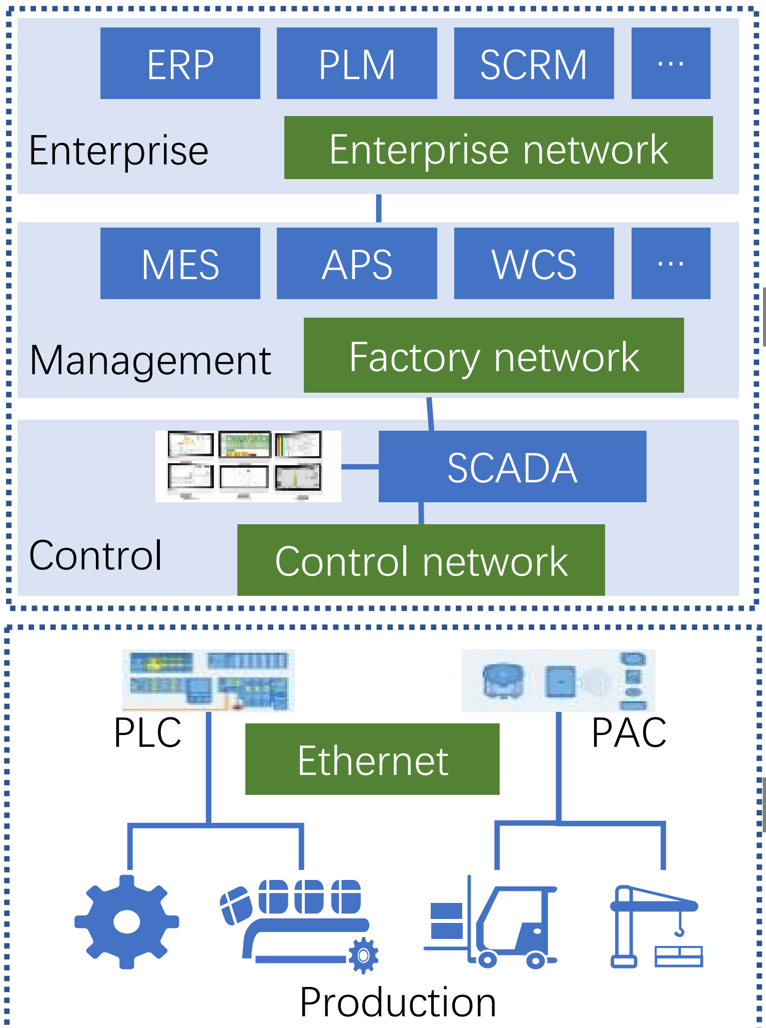
After a series of optimization and production line upgrade：

- Delivery time: increased by **7 days**
- Some key components' fabrication speed: increased **from 18s to 15s**
- Qualified products rate: increased by **5%**
- Energy consumption: reduced by **7%**
- Productivity increased: Euro 100,000/p to 360,000/p, **3.6 times**
- Total investment of 3.85 mi Euros has been repaid within **a year**

Contents

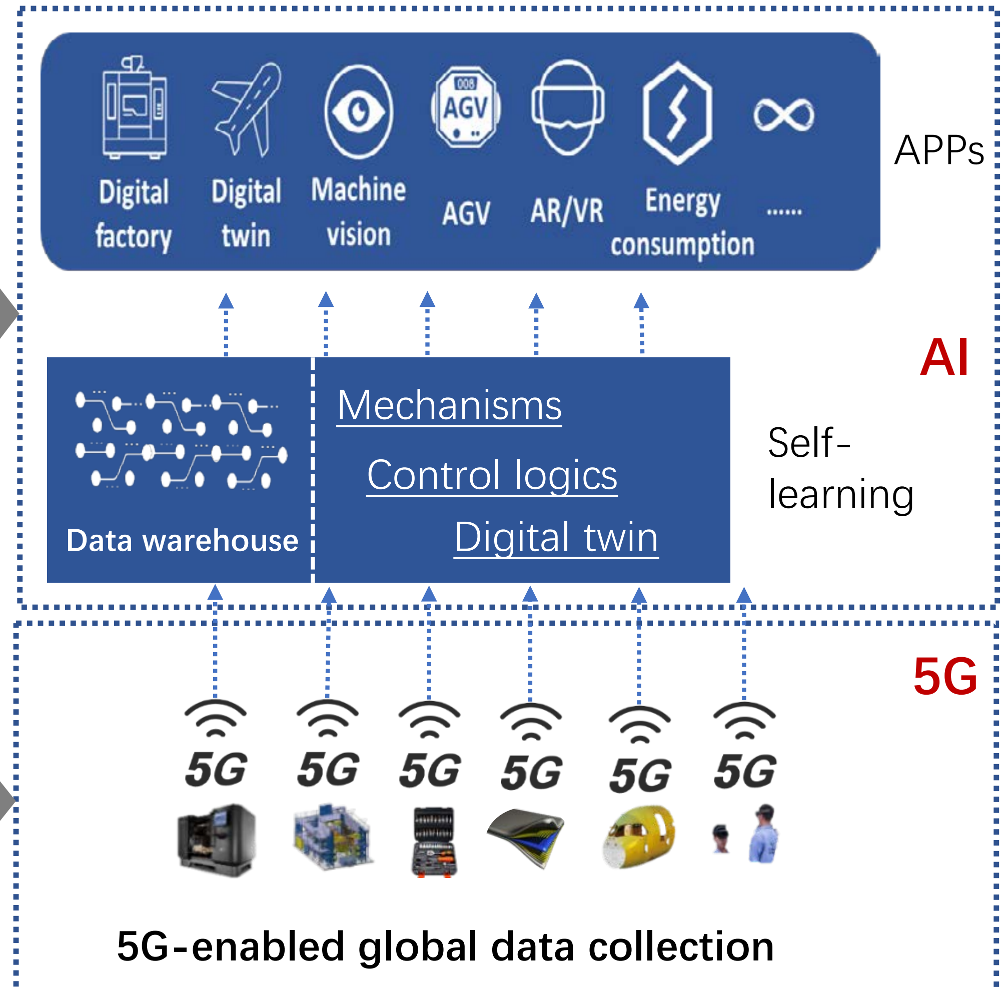
Data-driven Industrial Internet

Traditional industrial network



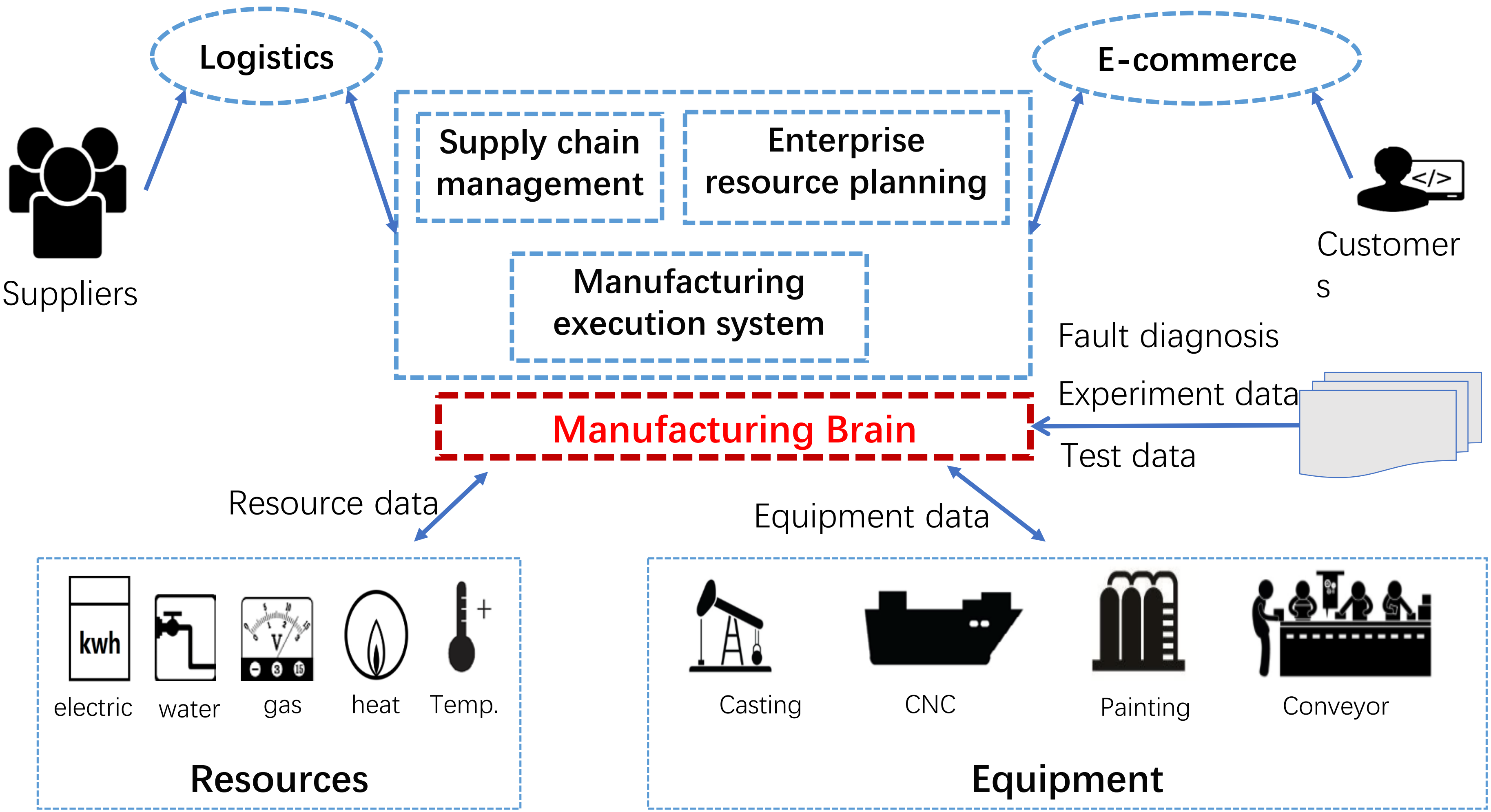
Local optimization, rule-based control

Data-driven industrial internet



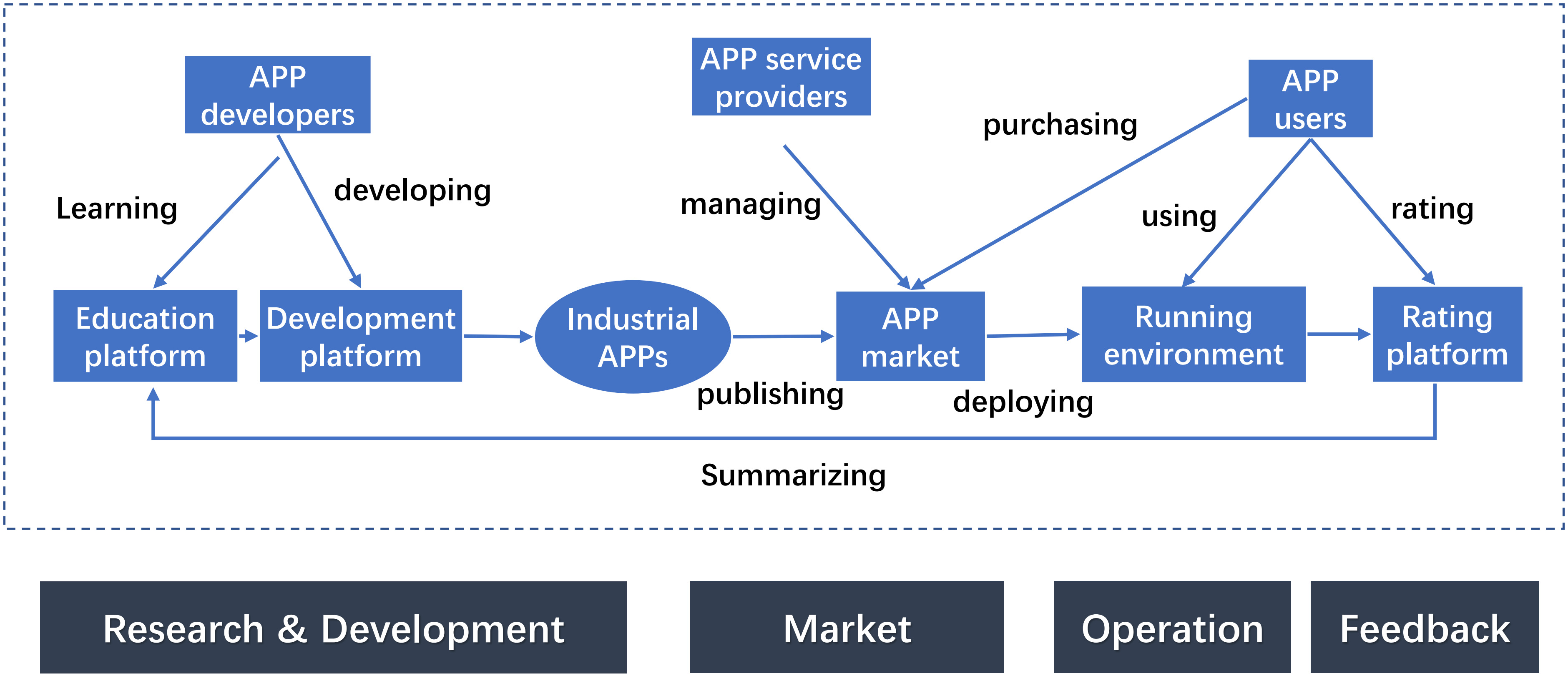
Global optimization, automatically discovering rules

Connecting All Enterprise Aspects



Smart Manufacturing Eco-system

Intelligent industrial APPs development and sharing



4 Steps towards Industrial Internet

1.0 Cloud

Resource

- Cloud computing

2.0 Internet

Architecture

- Internet middle-ware
- Platform strategy

3.0 Digital Twin

Data

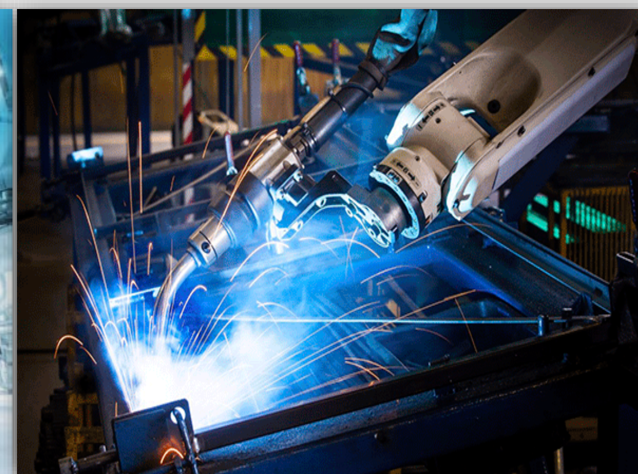
- Big data & AI
- Data management

4.0 Global Intelligence

Value

- Collaborative manufacturing
- Smart manufacturing
- Intelligent machines

Global Manufacturing Intelligence



Using 5G, massive heterogeneous manufacturing data can be transmitted to the central servers in real time.

Combining mechanisms and algorithms, global optimization can be achieved, and informed decision can be made in short time.

Discovering hidden trends and mechanisms with big data analytics for more accurate prediction of the potential problems may occur in the future.

Contents

- Why building industrial internet
- Industrial cases
- Future manufacturing paradigm
- Conclusions

Developing Collaborative Manufacturing

- Innovation： using platforms to combine the top strategy design and iterative bottom implementation
- Intelligence： ”mixed intelligence” integrating human and artificial intelligence
- Governance： data-driven and intelligent governance
- Development： digital economy leading consumption & service upgrade, manufacturing upgrade and supply chain upgrade

浙江大学
ZHEJIANG UNIVERSITY

Data and machine intelligence will not replace human beings

Machine intelligence will release human intelligence

Data comes from industry, returns to industry

Empowering Industry