

**‘Industry 4.0’ o ‘Fabbrica in evoluzione’ ?**

*ovvero*

**>> “Cosa sta succedendo qui per: **BigData/Analytics e Digital Twin**”<<**  
*(focus sulle PMI di Emilia/Romagna)*



# **BigData/Analytics & Internet-of-Things in Products Life-Cycle Management**

**- From Theory to Practice**

*Big data e data Analytics - Sfide ed opportunità per piccole e grandi aziende*

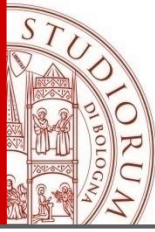


**Department of Computer Science and Engineering &**

**Department of Industrial Engineering  
Alma Mater Studiorum, University of Bologna**

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Prof. Eng. Marco Patella, Professor*

*October, 12th, Cineca Building*



# Agenda



- Business-Driven Analysis & Architecture
- Big Data System Architecture
- Computer Science & Industrial Engineering: Why together?
- Some Definitions
- From theory to practice:
  - Business Life-Cycle management (Automated Machine Industry)
  - Analytics in Failure Diagnostic, Trouble Shooting and Condition-based Maintenance (Automated Machine Industry)

# Business-Driven Analytics Architecture

## Dashboard & Synchronous GUIs

- OEE (per machine, line, factory)
- Euro (per part, per service, per machine)
- Travelled km (per part, per operator)
- Lead Time (service, delivery, retrieving)
- Sqm (storage space)
- Personnel
- Failures per Line, Machine, Factory
- ...



## Business Sensing & Acquisition

- Components
- Packaging
- Trucks & Deliveries
- Facilities & Warehouses
- Assembling Lines
- Machines
- ...

## Business Intelligence & Analytics (BI/BA)

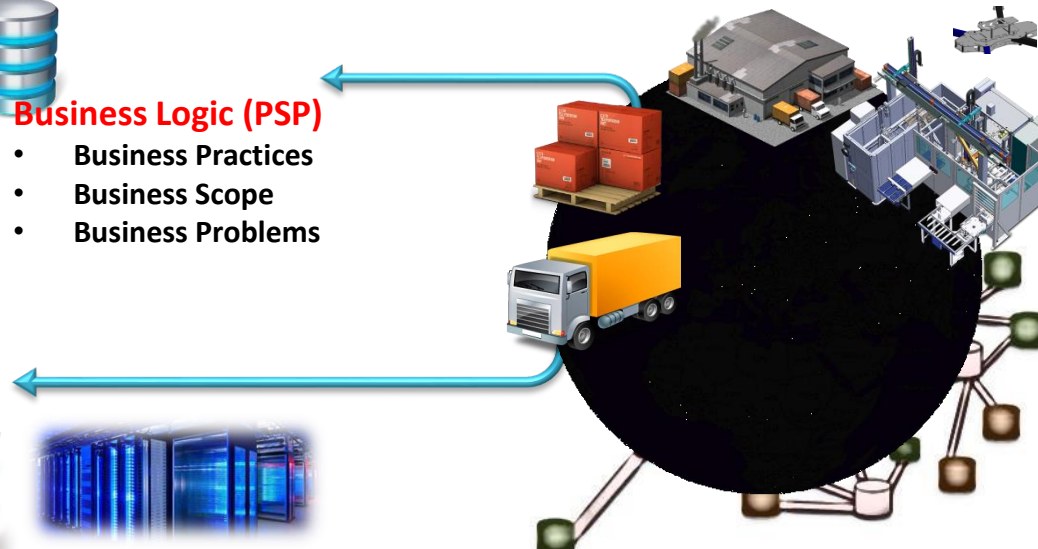
- Classification
- Clustering
- Algorithms
- Mining
- ...

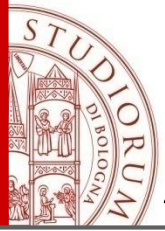


## Business Logic (PSP)

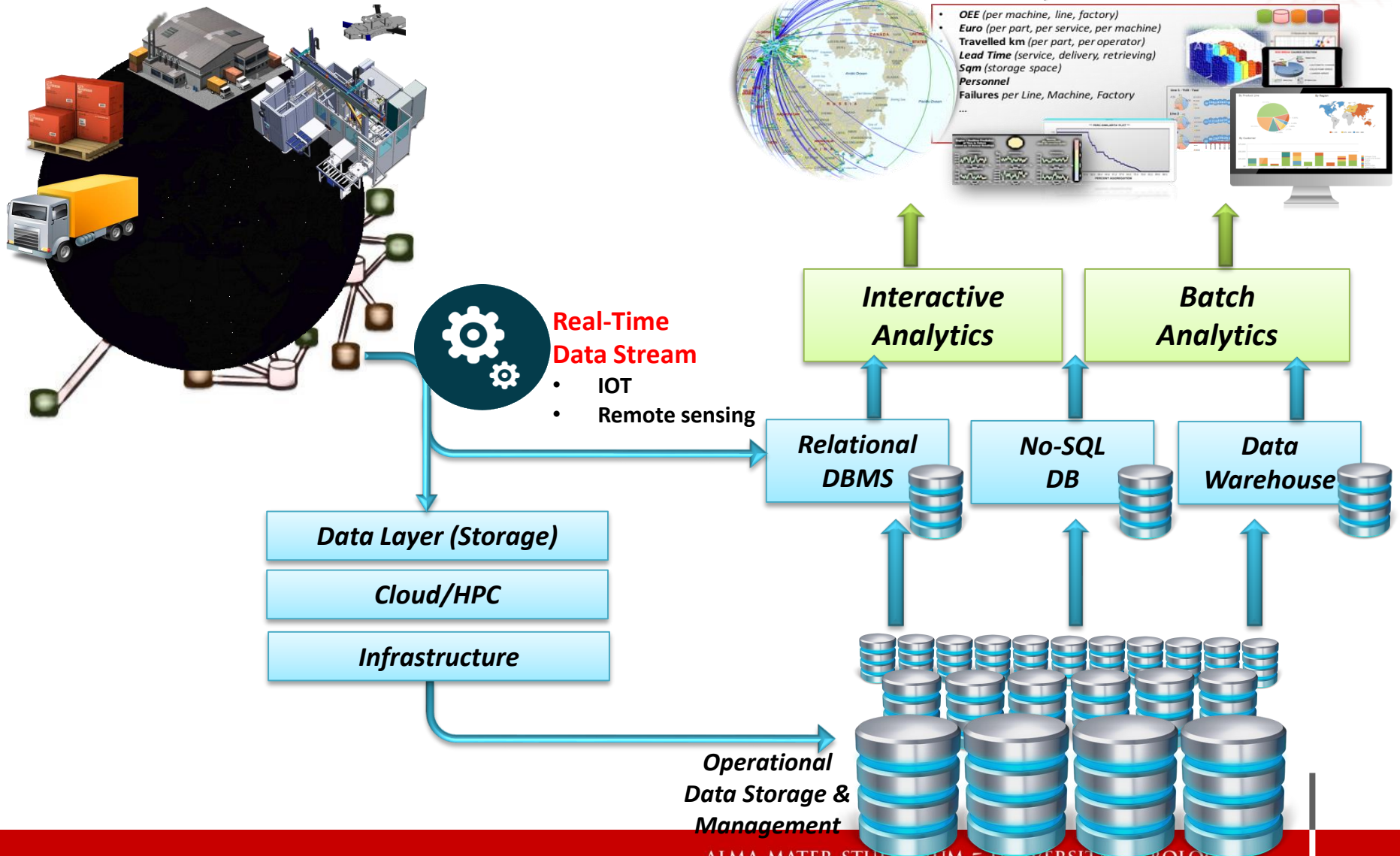
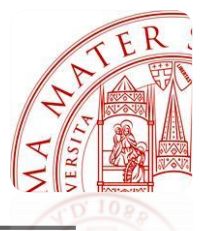
- Business Practices
- Business Scope
- Business Problems

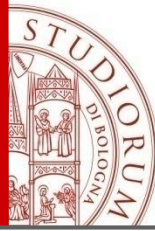
## Operational Data Storage & Management





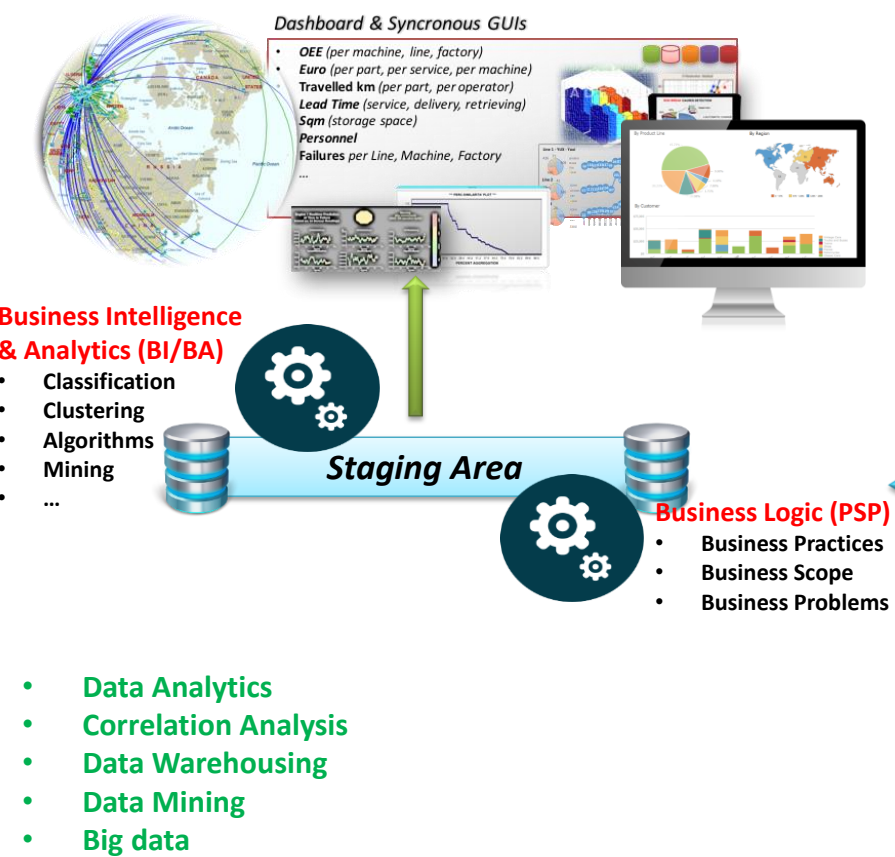
# Business Driven Big Data Architecture





# Industrial Engineering & Computer Science

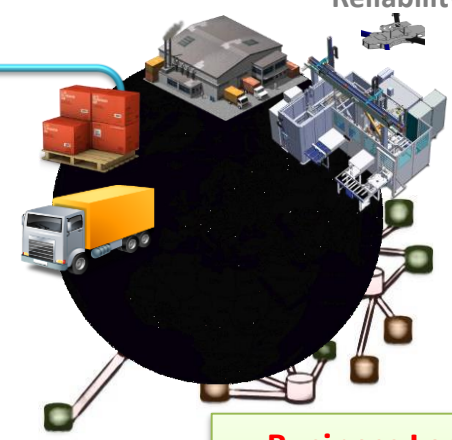
## Why together?



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## INDUSTRIAL ENGINEERING

- Operations management
- Manufacturing control
- Assembling system optimization
- Handling & Warehousing
- Distribution network design
- Event-driven Simulation
- Reliability & Maintenance Management



**Business Logic Understanding**

- Do I really know my problem?
- Are there proper models to address my problem?
- Could I customize this model to work for me?



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## COMPUTER SCIENCE AND ENGINEERING - DISI



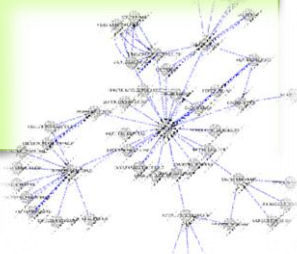
# Data Analytics Techniques (i)

## • Classification

- Identifying to which sub-population a new item belongs on the basis of a training set of items whose sub-population is known
- **App:** pattern recognition, biological/biometric classification

## • Associative Rules

- Discovering interesting relations between variables
- **App:** pricing/product placement, intrusion detection

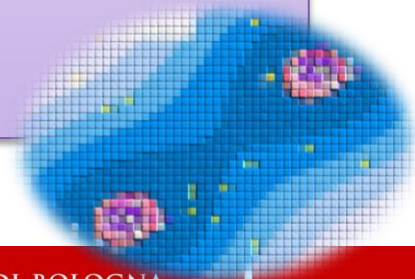


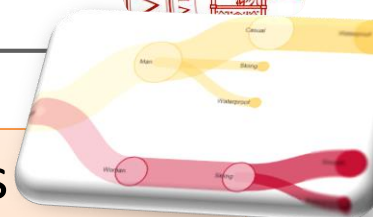
## • Clustering

- Grouping objects so that objects in the same group are more similar to each other than to those in other groups
- **App:** market research, grouping of shopping items/customers

## • Outlier Detection

- Identification of items which do not conform to an expected pattern
- **App:** intrusion/misuse detection, fraud discovery





## • Time Series Analysis

- Analyzing time series data to extract meaningful statistics and other data characteristics
- **App:** Forecasting, classification

## • Text Mining

- Deriving high-quality information from text
- **App:** Indexing, customer relationship management

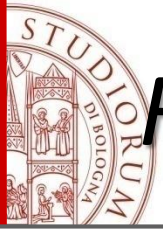


## • Clickstream analysis

- Recording of the parts of the screen a computer user clicks on while web browsing
- **App:** Market research, employee productivity

## • Sentiment analysis

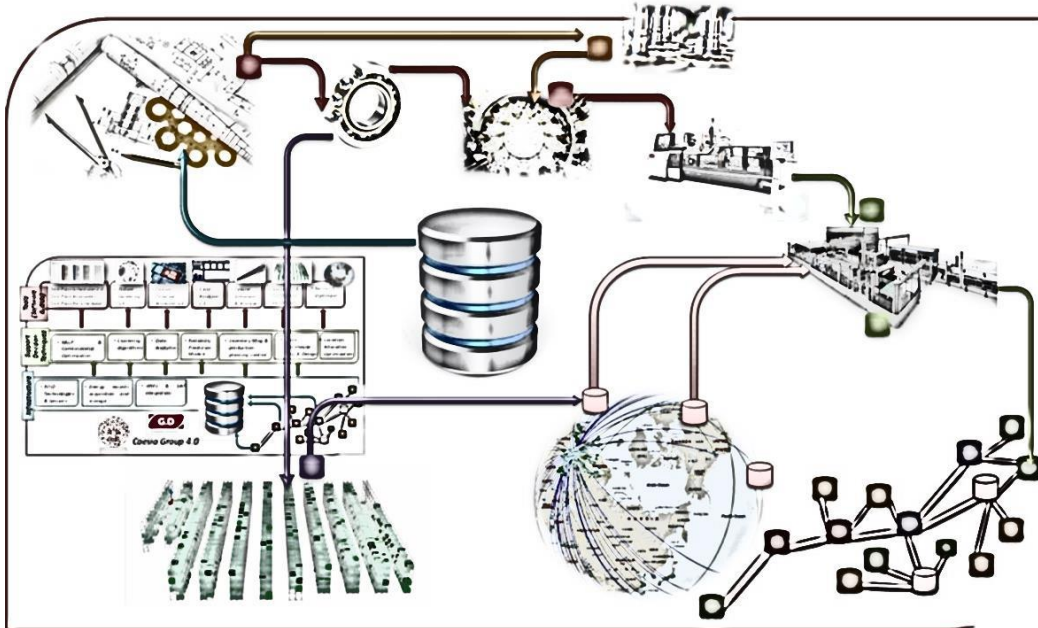
- Identifying and extracting subjective information in source materials
- **App:** Enterprise/product reputation



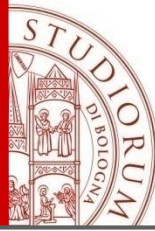
# From Theory to Practice



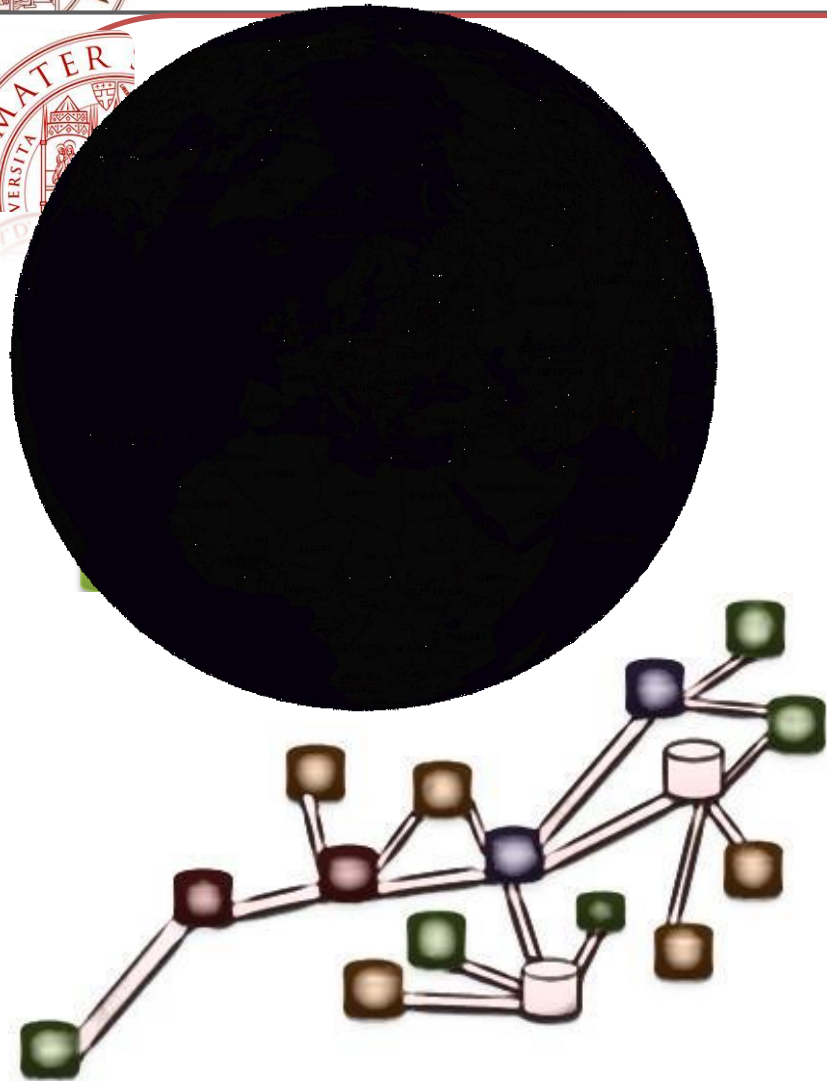
## Business Life-Cycle Management







# From IOT to IOLM (Internet Of Logistics & Maintenance)



**Factories**

- Lines & machines installation
- Training customer operators
- Ordinary and corrective maintenance
- Maintenance services & spare parts demand



**Regional Maintenance Service Provider (MSP)**

- Spare parts management and fulfillment
- Maintenance service delivery (Preventive, Corrective, etc.)



**Spare parts supplier**

- Spare parts manufacturing & supplying
- Spare inventory management



**Distribution center**

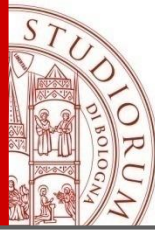
- Spare parts warehouse
- Order picking and storage efficiency
- Packaging issues



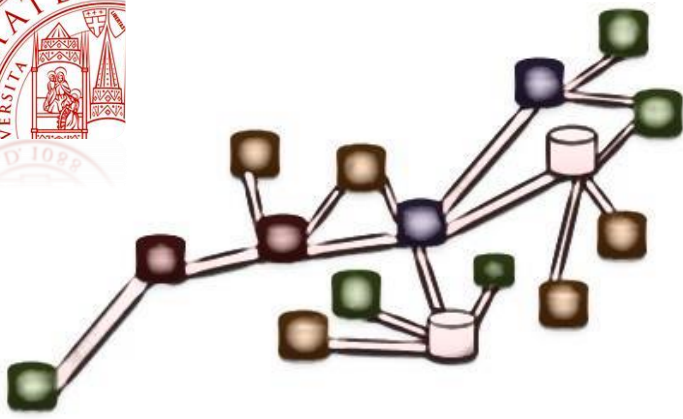
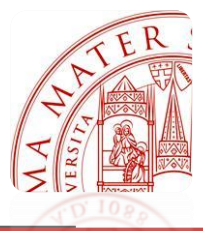
**Business Plant**

- Production system management
- Lot per lot/batching scheduling
- Personell management





# From IOT to IOLM (Internet Of Logistics & Maintenance)



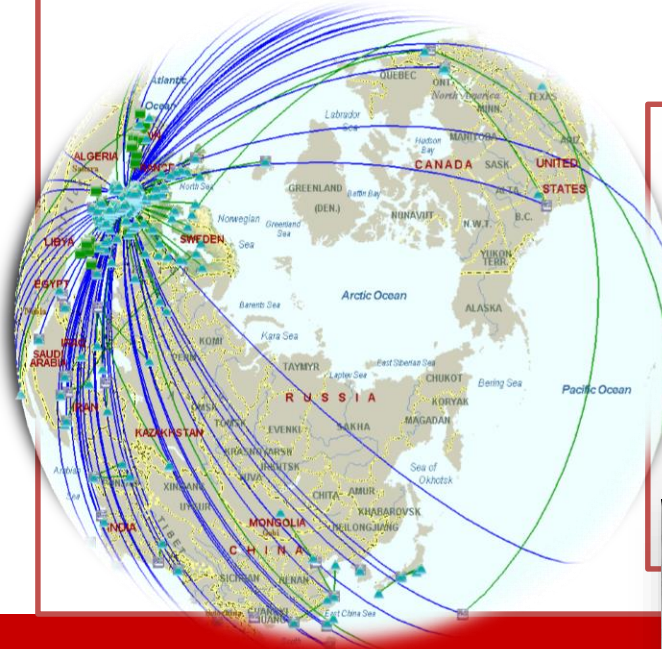
**Factories**

**Regional Maintenance Service Provider (MSP)**

**Distribution center**

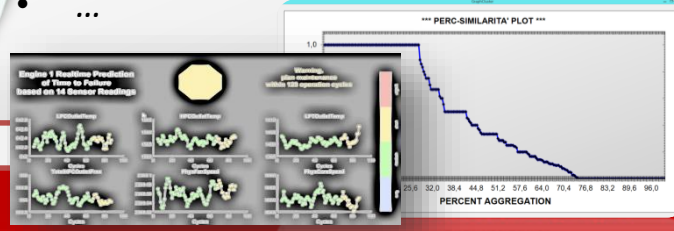
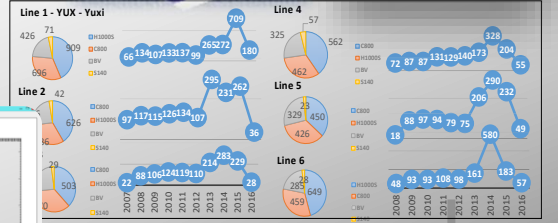
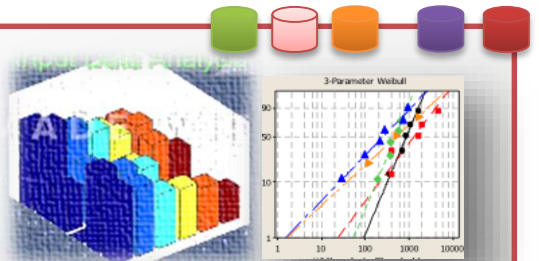
**Spare parts supplier**

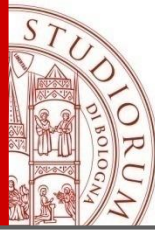
**Business Plant**



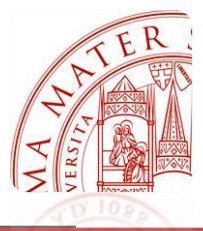
## Dashboard & Synchronous GUIs

- **OEE** (per machine, line, factory)
- **Euro** (per part, per service, per machine)
- **Travelled km** (per part, per operator)
- **Lead Time** (service, delivery, retrieving)
- **Sqm** (storage space)
- **Personnel**
- **Failures per Line, Machine, Factory**
- ...





# From IOT to IOLM (Internet Of Logistics & Maintenance)



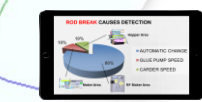
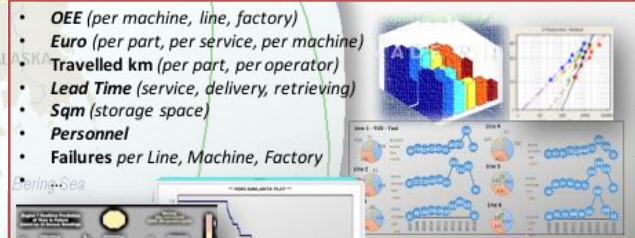
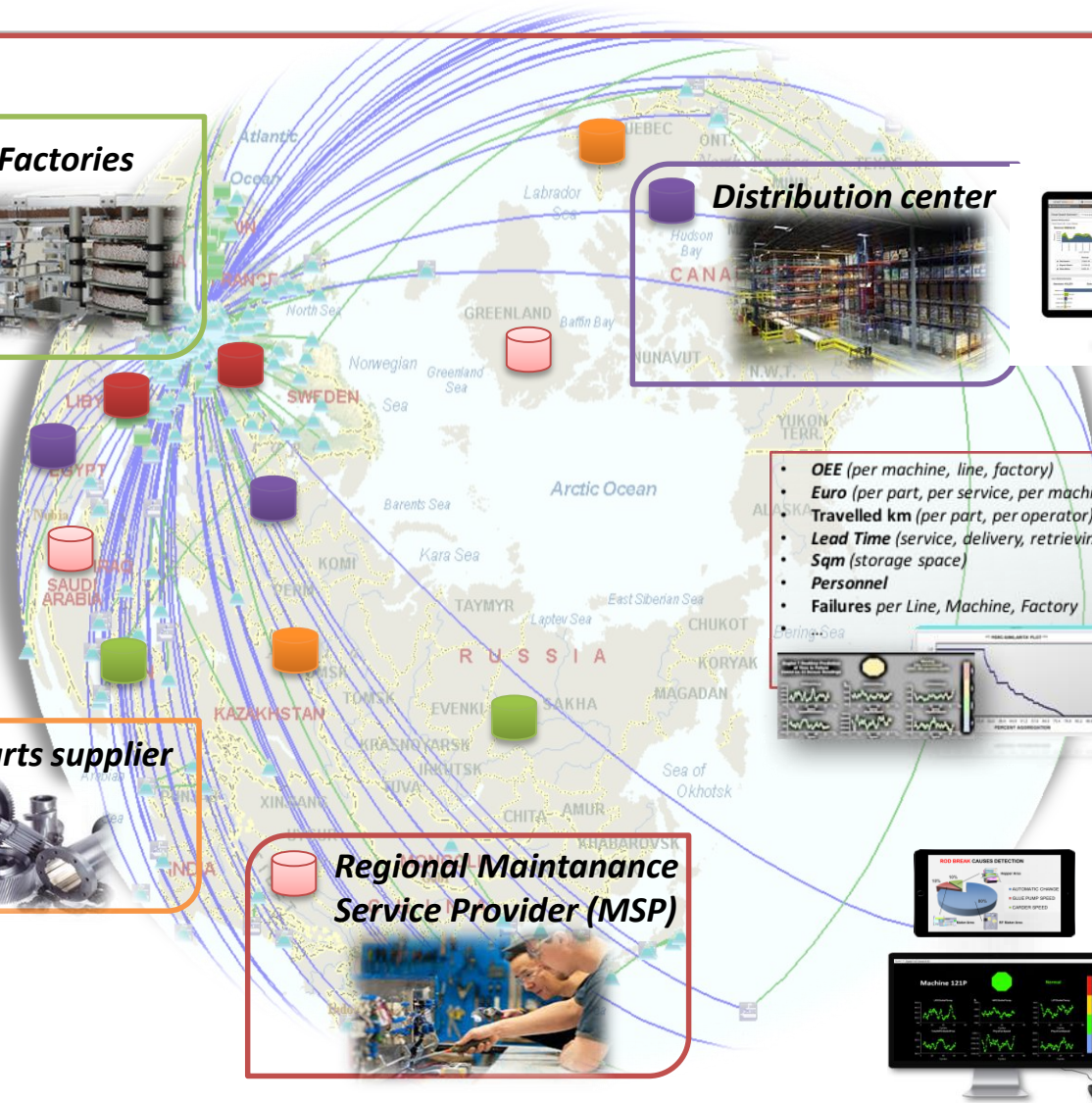
**Factories**

**Distribution center**

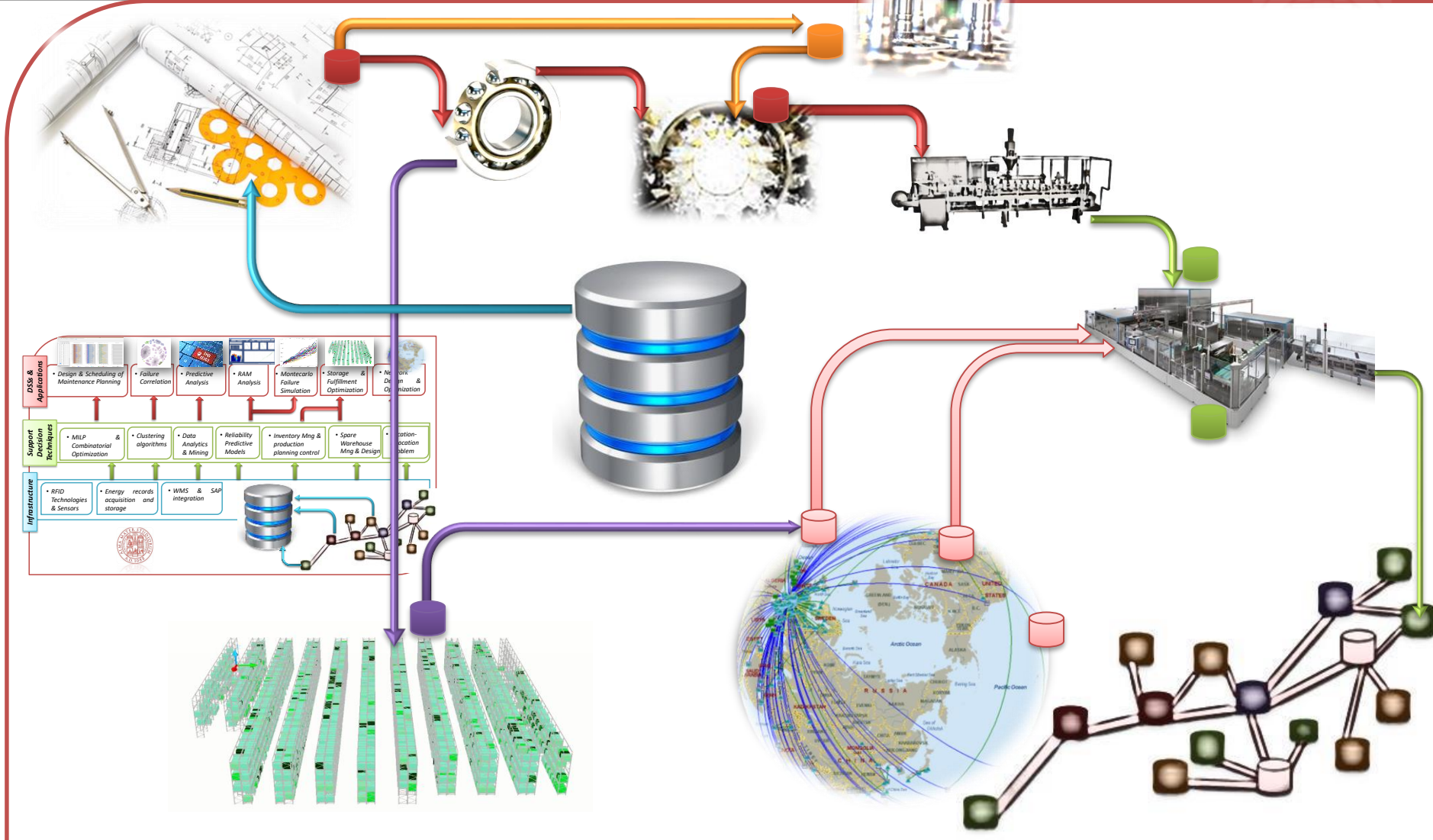
**Spare parts supplier**

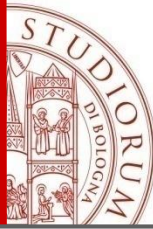
**Regional Maintenance Service Provider (MSP)**

**Business Plant**

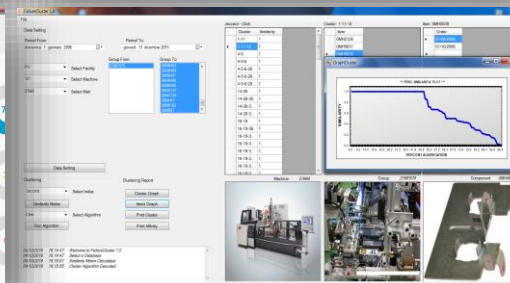
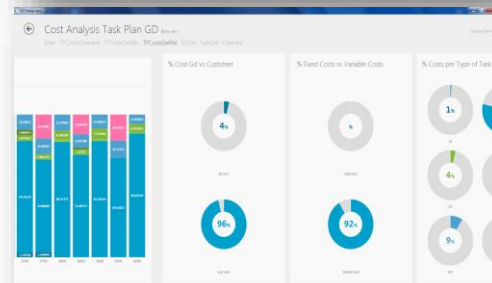
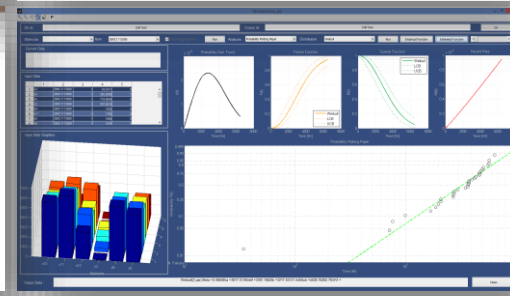
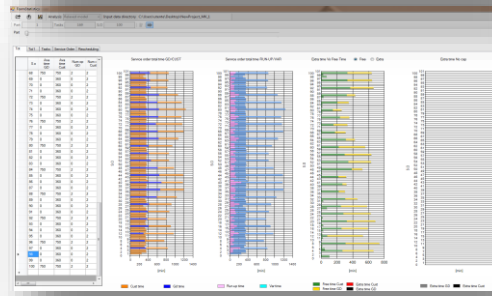
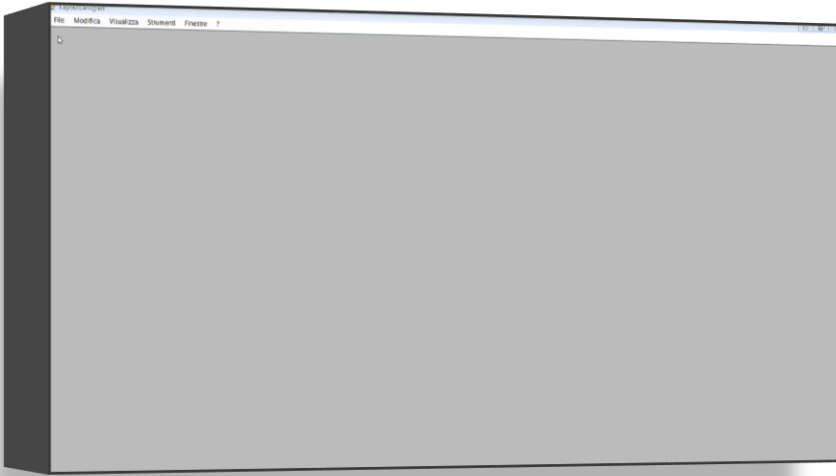
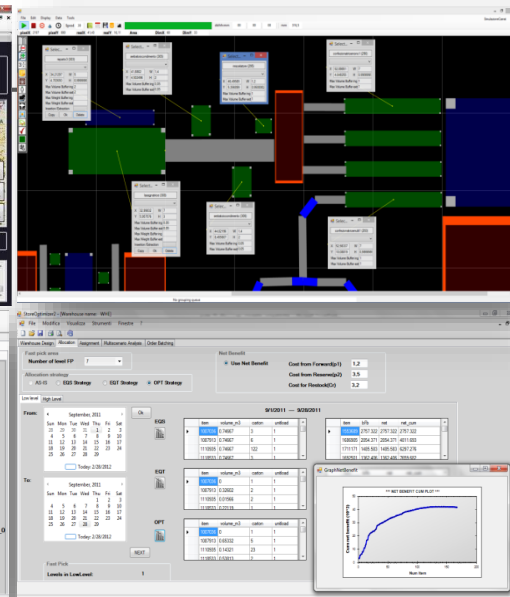
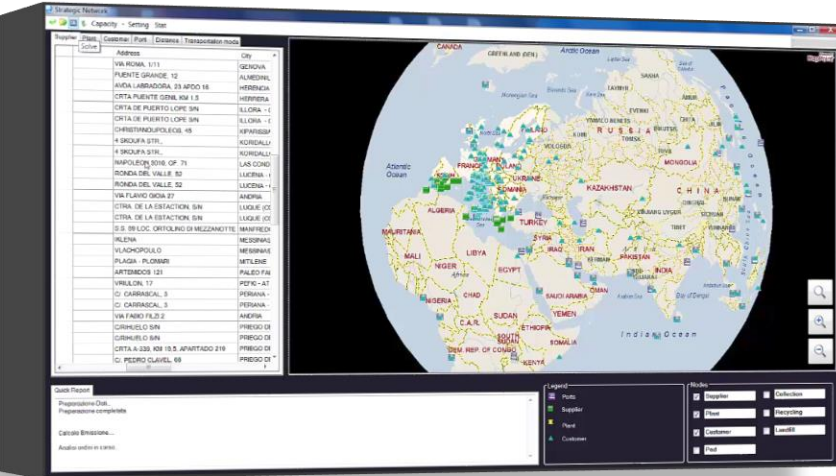


# From IOT to IOLM – Accounting Component Life Cycle

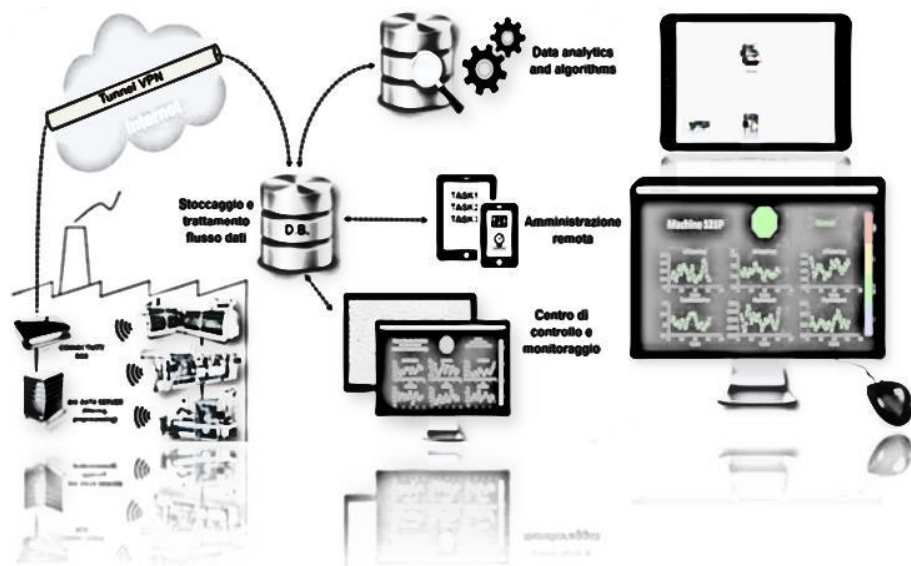




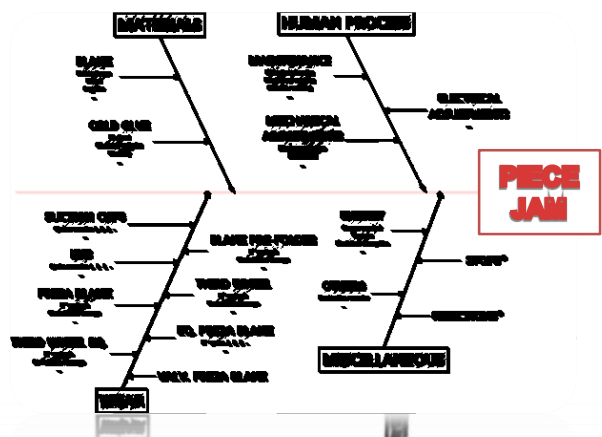
# Tools & GUIs for Business Life Cycle Management



## Analytics in Dailure Diagnostic, Trouble Shooting and Condition-based Maintenance



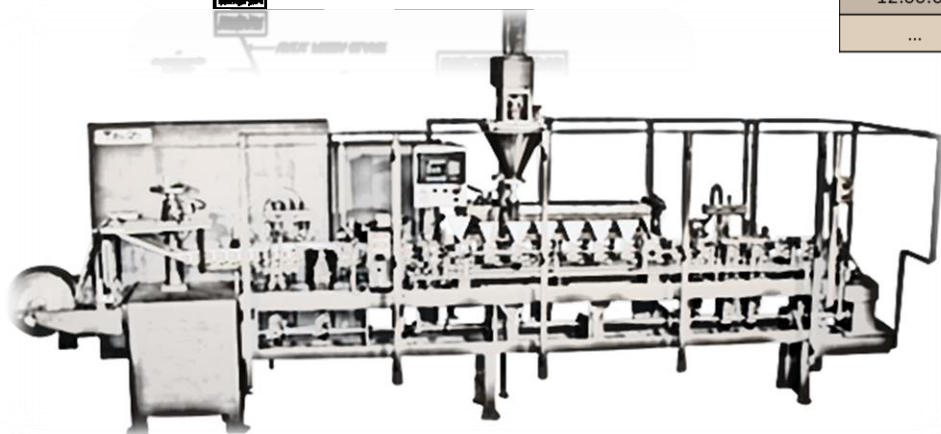
- Develop robust models to **Predict** failures and avoids stops, System **Diagnostic**, and aid **Troubleshooting**.
- Analyzing the **historical** machine working status to predict whether the machine status will be Normal or Critic in the next minute.



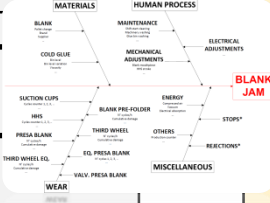
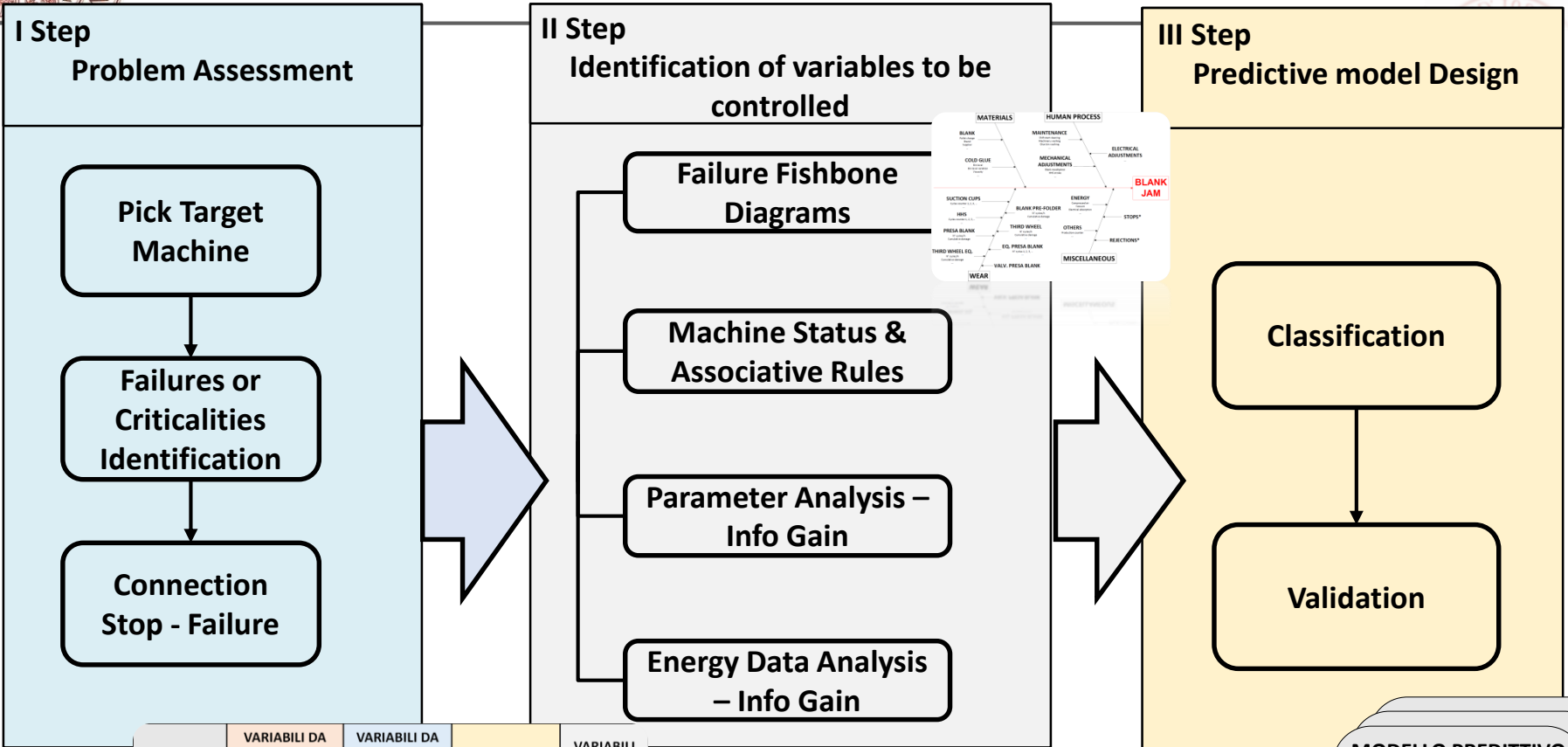
TIMESTAMP	VAR 1	VAR 2	...	VAR N
12:00:01	0.002	TRUE	...	5
12:00:02	0.003	TRUE	...	5.5
12:00:02	0.126	FALSE	...	6
...	...	...	...	...



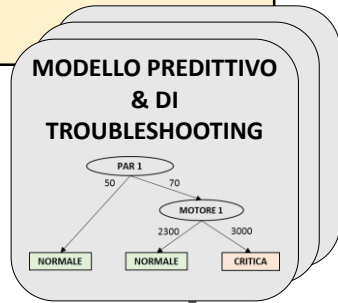
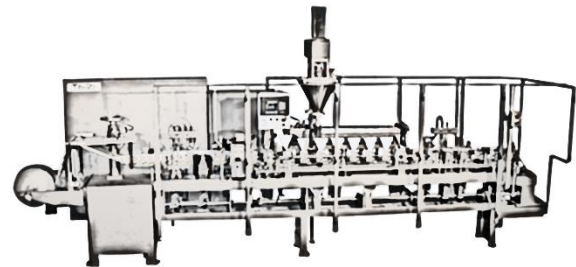
- Condizione **NORMALE**
- Condizione **CRITICA**
  - Causa 1
  - Causa 2
  - ...
  - Causa N



# Step of Analysis

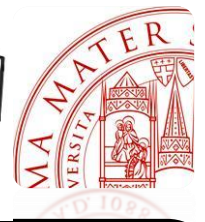
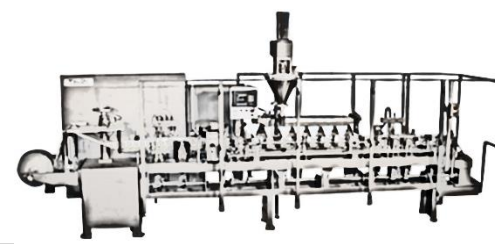


TIMESTAMP	VARIABILI DA DIAGRAMMA FISHBONE					VARIABILI DA REGOLE ASSOCIATIVE					PARAMETRI					VARIABILI DI ENERGY			
	A	B	C	D	E	A	B	C	D	E	1	2	3	4	5	A	B	C	D
12:00:01	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
12:00:02	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
12:00:02	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
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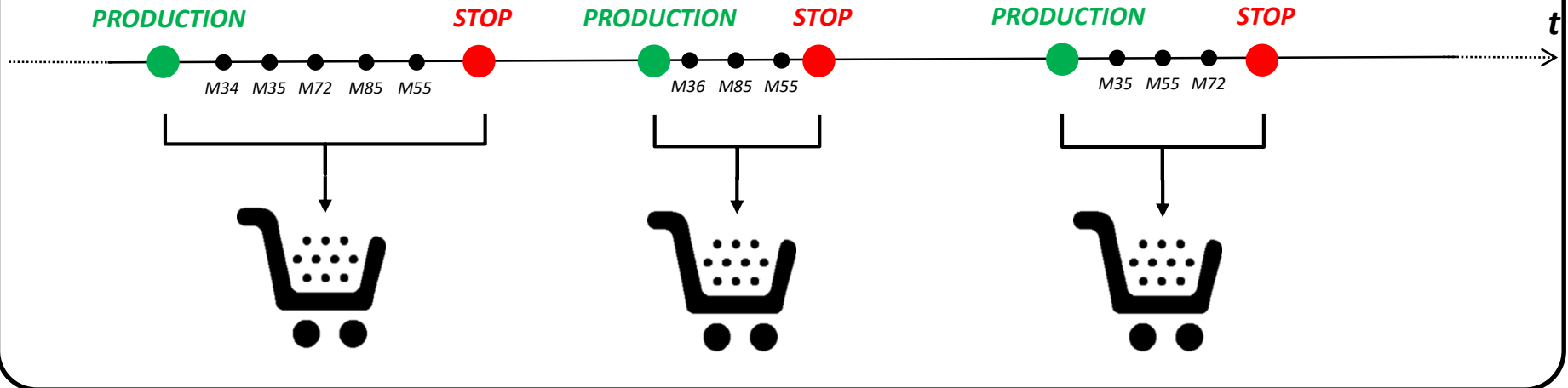




# Associative Rules



## Building «Basket» of Machine Status before Stops



### OCCURENCES SEARCH (Apriori)

1. Analysis of the unordered baskets.
2. Assessment of the obtained results with team of workers UT/PPO/GT

#### Example

LOWER REEL RELEASED – MAKER -> ROD BREAK (45% dei RB totali\*)

Relationship Cause-> Effect

EXCESSIVE PIECE REJECTION – CID -> ROD BREAK (89% dei RB totali\*)

Relationship Effect-> Effect

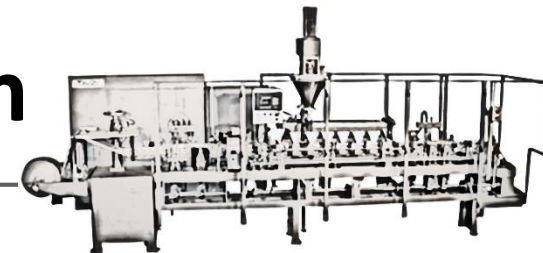
### FREQUENT SEQUENCES SEARCH (GSP)

1. Analysis of the ordered baskets.
2. Assessment of the obtained results with team of workers UT/PPO/GT

#### Example

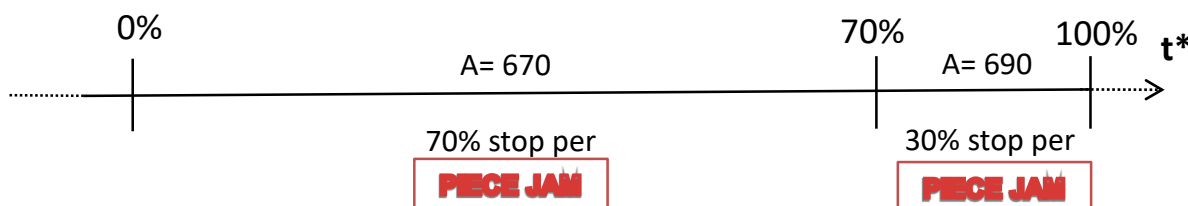
NOMINAL SPEED -> LOW PROD. SPEED -> PIECE JAM  
(16% dei BJ totali\*)

# Parameter Analysis – Info Gain



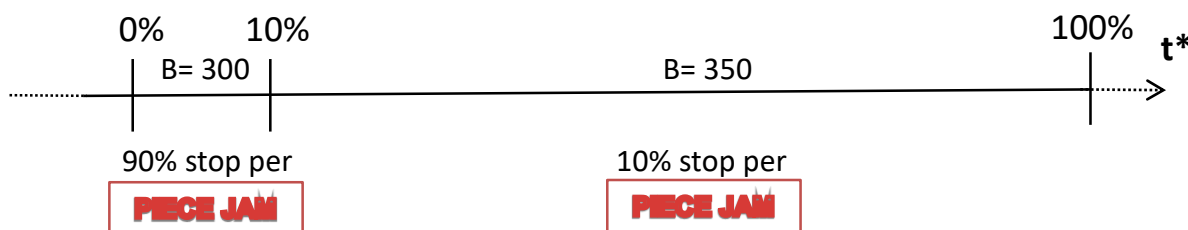
## Example of Info-Gain:

- Case 1: parameter A



Low Info Gain

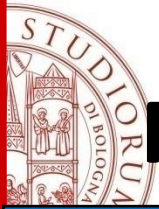
- Case 2: parameter B



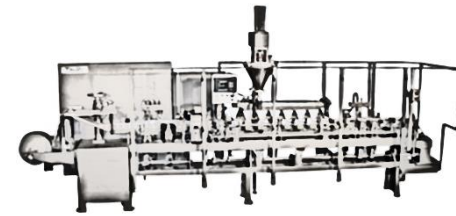
High Info Gain

## Scopes:

- Identify those parameters presenting High Info Gain in order to not affect the analysis and increase the accuracy of the predictive model.
- Assess critical values for the identified parameters and aid machine settings accordingly.



# Parameter Analysis – Info Gain

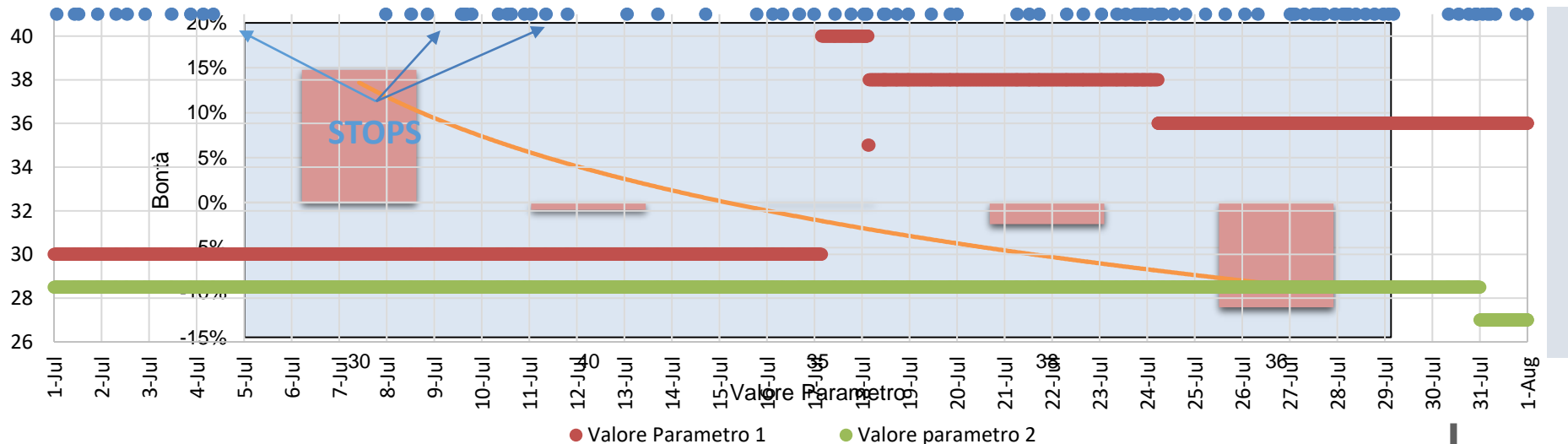


PARAMETER	VALUE	START	PERIODS (Day)	%TIME	N° STOP	%STOPS	GOODNESS
Parameter 1	30	7/1/16 0:00	16.02	51.68%	381	36.92%	14.76%
Parametro 1	40	7/17/16 3:14	0.97233	3.50%	41	3.97%	-0.84%
Parametro 1	35	7/18/16 2:40	0.02488	0.09%	0	0.00%	0.09%
Parametro 1	38	7/18/16 3:16	6.08941	22.16%	226	21.90%	-2.54%
Parametro 1	36	7/24/16 5:24	6.99227	22.56%	353	34.21%	-11.65%
Parametro 2	2850	7/1/16 0:00	30.0045	96.79%	977	94.67%	2.12%
Parametro 2	2700	7/31/16 0:06	0.99553	3.21%	55	5.33%	-2.12%

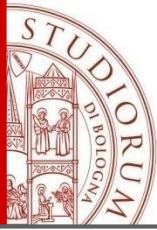
Info Gain = 29,88

Info Gain = 4,24

## IMPRELAZIONE PARAMETRI - STOP



- Parameter 1 is the best for the classification algorithms
- The value 36 of Parameter 1 is critical to the observed problem (Failure)



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COMPUTER SCIENCE AND ENGINEERING - DISI

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