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Applied Business AI - From the Dark Ages to Agentic Future

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ICT CLUSTER VARNA

BSMEPA BULGARIAN SMALL AND MEDIUM ENTERPRISES PROMOTION AGENCY

BAPHA

BRAIN++ AI FACTORY

ARC FUND

A pioneering application of using neural networks in industry

Developed in 1993 at the Texaco StarEnterprise refinery in Delaware City, Delaware

Pergamon

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ON-LINE EXPERT SYSTEM FOR ODOR COMPLAINTS IN A REFINERY

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Abstract - On-line capabilities of modern expert systems are of special interest due to the possibility of real-time environmental monitoring and detection of possible rules violations in their early phase of development. One of the most difficult environmental problem for some refineries located in fairly populated areas are released refinery odors. In an attempt to solve this problem, an odor expert system is proposed in this paper. It includes a historical data base with all available odor complaints, real-time monitoring of weather data and selected process variables, a detailed map, and rules. The rules are based on the developed methodology for quantitavely correlating process variables with odor complaints. The methodology includes threshold values calculations for selected variables at the Waste Water Treatment Plant and their correlation with process variables in different units inside the refinery. The proposed expert system has been implemented in the GENSYM G2 software environment at StarEnterprise refinery in Delaware City, Delaware, USA.

Table 3. Neural network predictions results for NH3

NN Structure	R^2	Mean predicted error (%)	Max predicted error (%)
10inputs-16hidden-1output	0.92	4.6	29.5
4inputs-16hidden-1output	0.89	5.3	27.3
4inputs-2hidden-1output	0.91	4.7	17.7

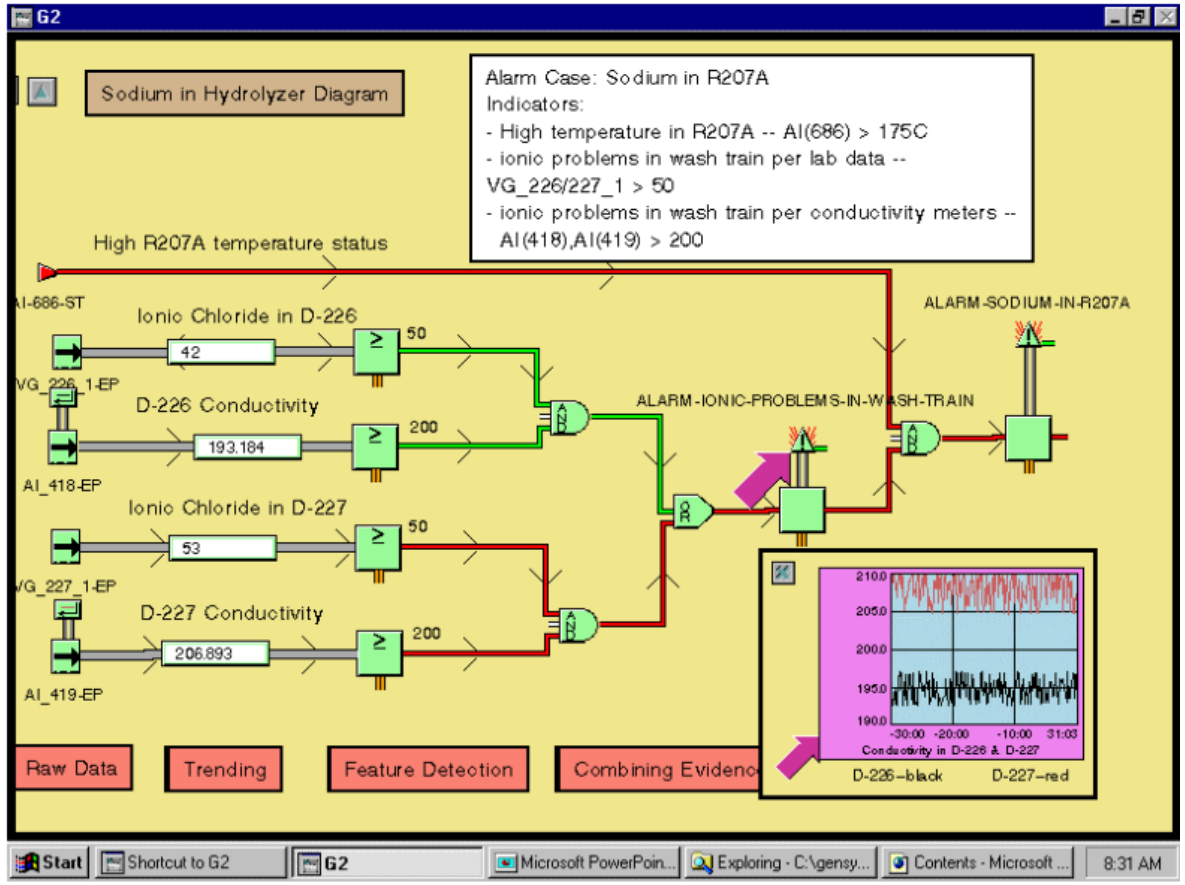
The first structure includes as inputs the values of the five internal NH3PM for the current and the previous days, 16 neurons in the hidden layer (as recommended by NEUROSHELL2 package), and one output - NH_3PM at the WWTP the next day. After analyzing the influence of different inputs on the output result, it has been found that three of the inputs have negligible influence and another structure with four inputs has been trained. The performance of this neural network was reduced insignificantly. Finally the data set was processed by an genetic algorithms optimizer that confirmed the rejected inputs and reduced the number of the hidden layer neurons to two. This is the structure that was selected for prediction of NH_3PM at the WWTP.

CONCLUSIONS

An expert system for analyzing odor complaints and predicting possible odor release from a refinery was developed. Odor-related thresholds on selected process variables at the WWTP are calculated in order to give maximal prediction of available odor complaints. Fore some process variables inside the refinery a neural network model has been developed that links these variables to the odor-related thresholds. With this approach it is possible to activate an alarm rule one day in advance if the odor-related threshold will be violated.

An example of an applied expert system for intelligent alarms handling (1997)

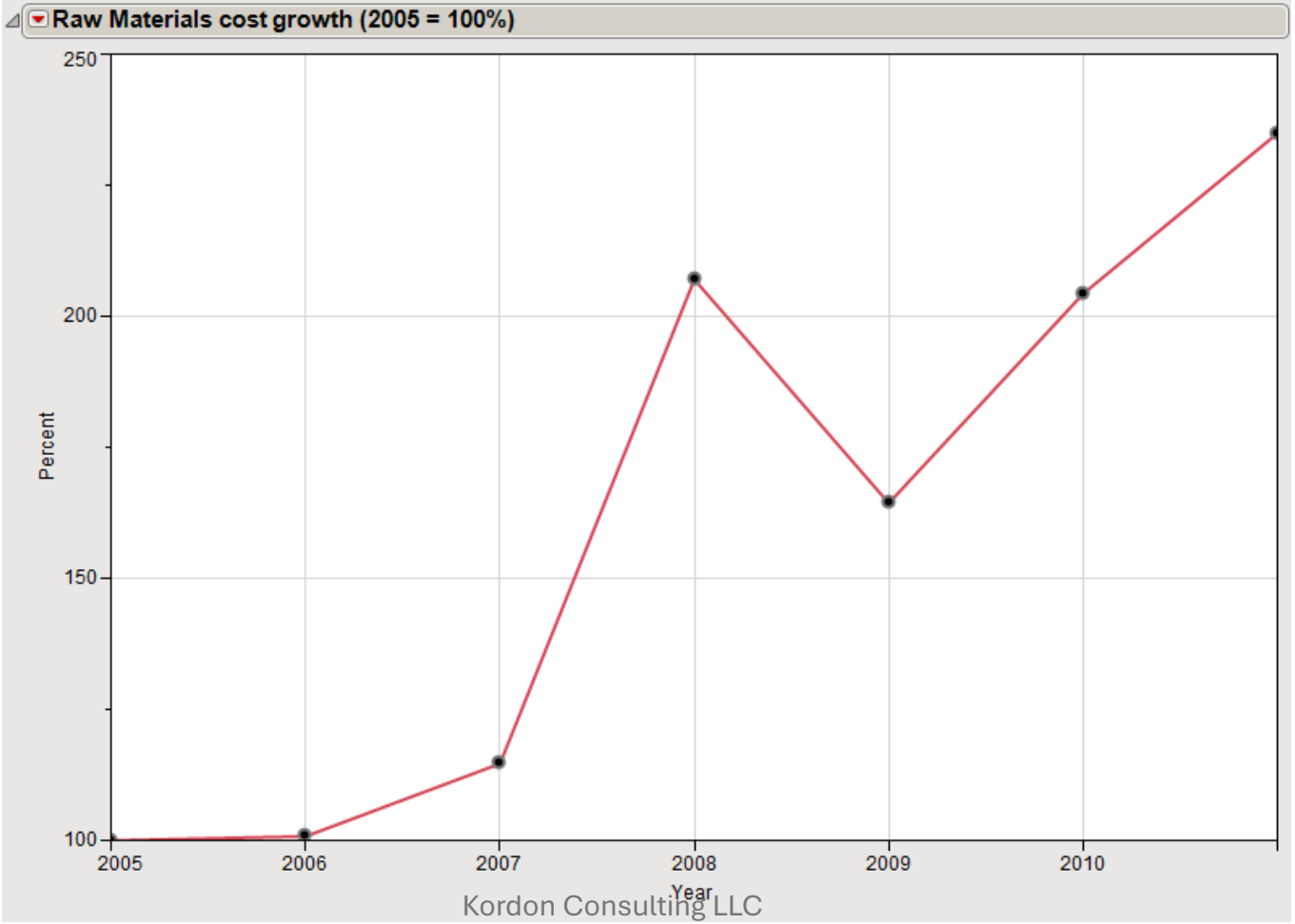
Alarm logic diagrams integrate expert's knowledge with process data and developed models



Developed in 1997 at the Dow Chemical Epoxy plant in Freeport, TX

Use case example with high economic impact: Raw Materials Price Forecasting

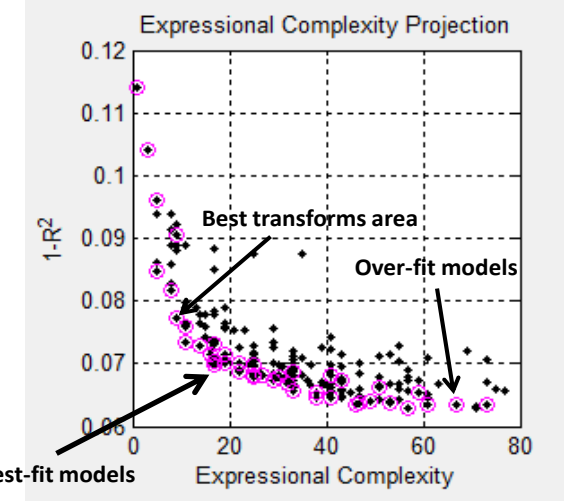
Dow Chemical Raw Materials Cost Growth (2005 – 2011)



Nonlinear Forecasting = Genetic Programming (GP) + ARIMAX

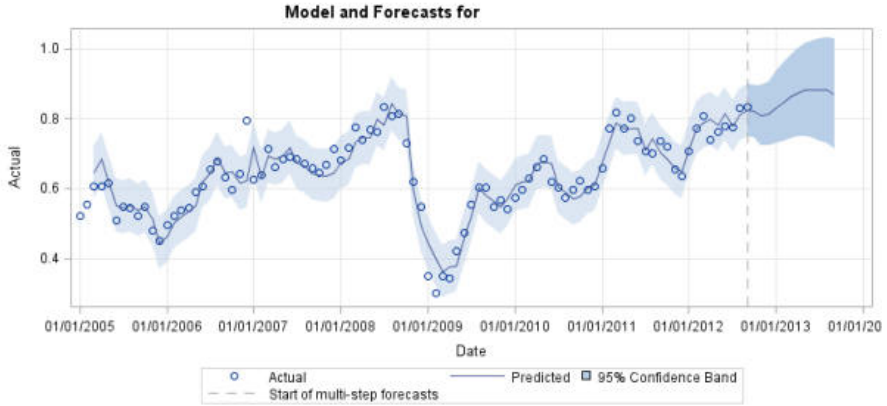
Genetic Programming

Variable selection
Nonlinear transforms



ARIMAX

Forecasting using nonlinear transforms



Simple transform example

$z(t) = x_2(t-2)*x_3(t-1)$

Nonlinear ARIMAX

$y(t) = a + b*y(t-1) + c*z(t) + d*e(t-1) + e(t)$

Most forecasting models predicted with ~ 10% error

1	2	3	4	5	6	Model Error
0.4%	0.7%	0.9%	1.1%	1.2%	0.5%	0.8%
1.1%	1.6%	1.5%	0.8%	1.0%	0.1%	1.0%
0.9%	2.4%	2.9%	2.5%	0.3%	2.3%	1.9%
0.8%	0.9%	1.5%	1.5%	2.9%	4.1%	2.0%
1.6%	2.6%	2.9%	2.2%	1.0%	1.5%	2.0%
3.0%	5.1%	7.7%	6.5%	5.8%	1.4%	4.9%
3.3%	4.4%	4.6%	5.4%	7.6%	5.8%	5.2%
8.0%	8.3%	1.2%	2.1%	5.7%	6.2%	5.2%
8.5%	9.9%	8.0%	8.6%	14.2%	20.6%	11.6%
4.0%	7.0%	11.6%	17.0%	22.4%	24.2%	14.4%
11.7%	12.7%	16.0%	20.8%	16.0%	24.9%	17.0%
6.0%	14.1%	18.5%	18.6%	19.5%	36.2%	18.8%
19.9%	18.4%	15.4%	16.0%	31.8%	39.3%	23.5%
39.1%	39.6%	41.1%	41.0%	38.6%	37.6%	39.5%
7.74%	**9.11%**	**9.56%**	**10.29%**	**11.99%**	**14.61%**	**10.55%**

pred error < 5%
5% < pred error < 10%
10% < pred error < 15%
15% < pred error < 20%
pred error >20 %

Color code

The average cost of raw materials is ~ $5 billion/year
Average savings of 2.5 % can save ~$125 million/year

Average Mean Absolute Percentage Errors for all prices for a month-ahead forecast

Use case example with high economic impact:
Predictive maintenance: Reducing paper machine breaks



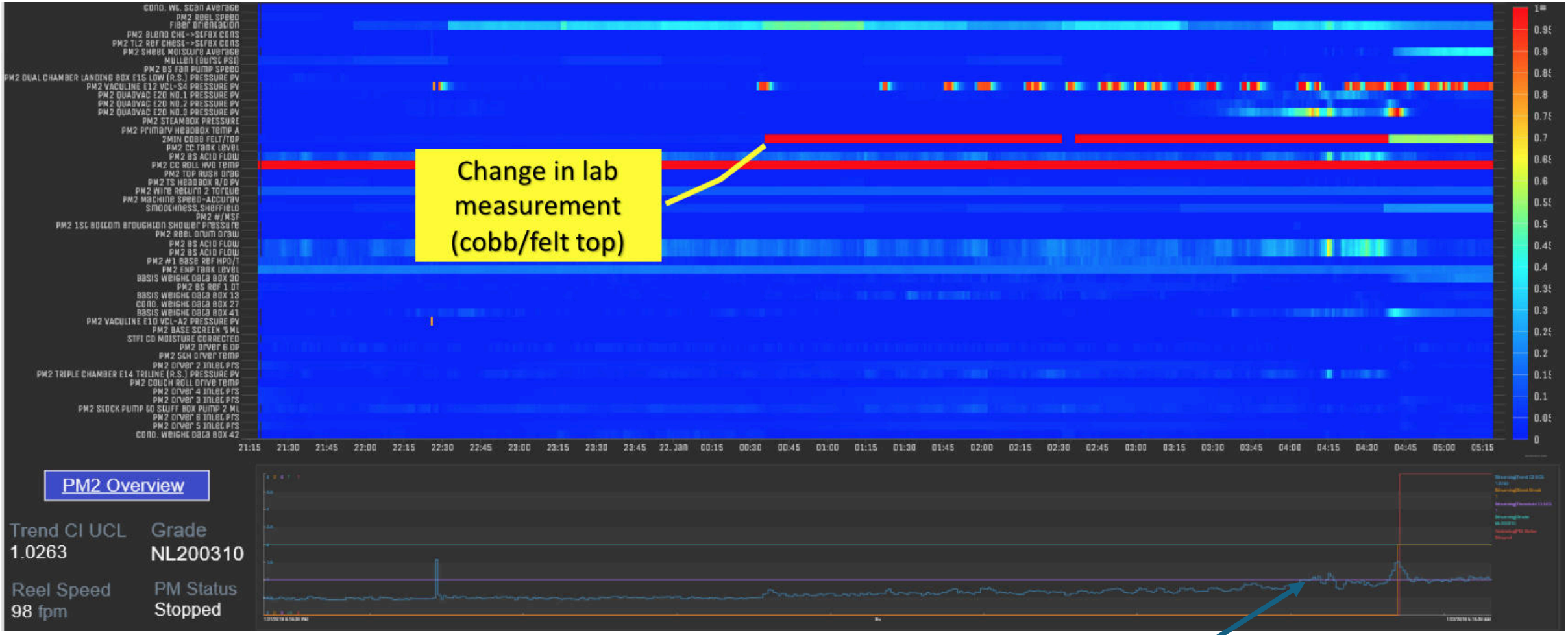
Paper machine

Paper machine breakdowns led to 1.6 hours average loss of production time per day, which amounts to $6–8 million per year for each production line.



Stops after paper machine break

Predictive paper machine breaks: Real-time system operation

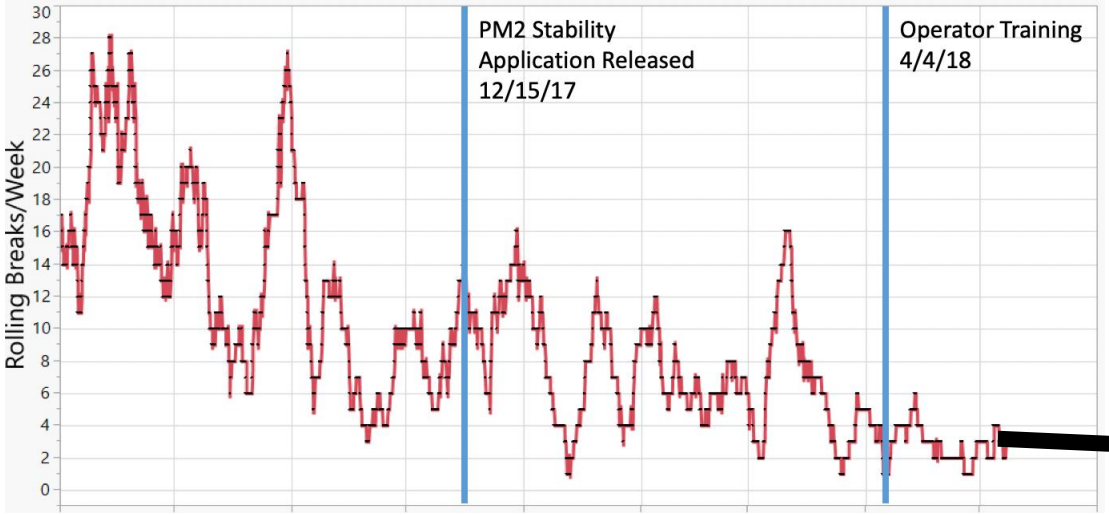


Machine health monitor

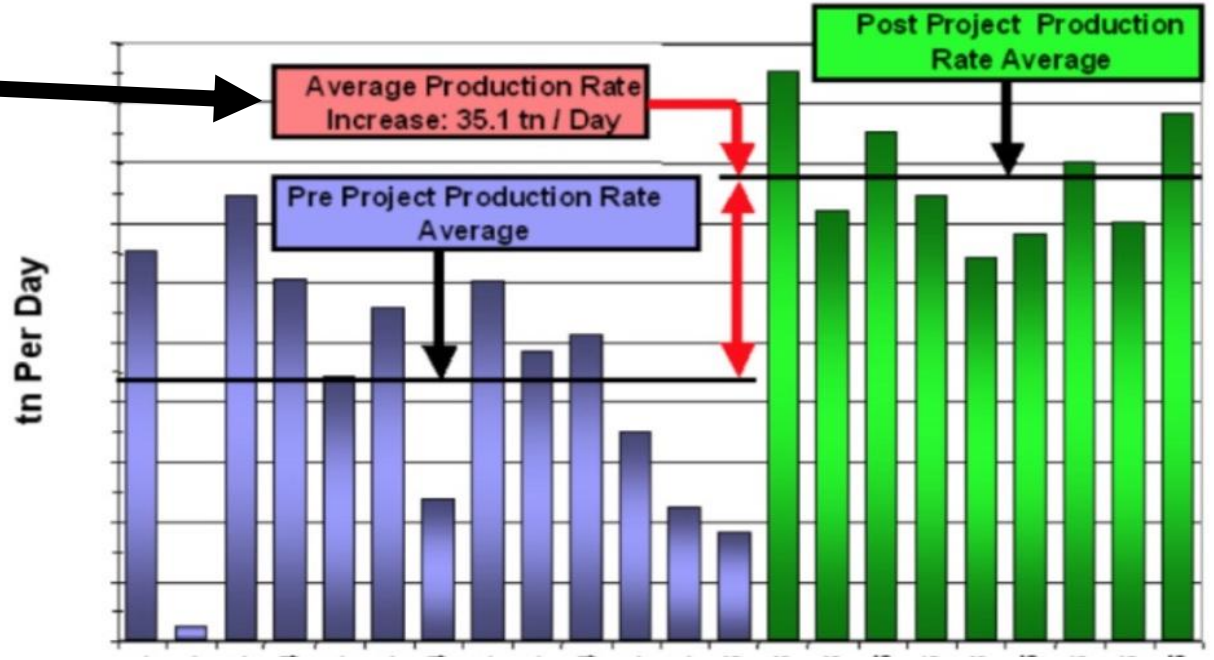
Crossing red line raises alarm

Applied AI value creation by increasing productivity

Leveraged on 26 machines



Increased productivity of a paper machine due to reduced breaks by AI-based predictive maintenance



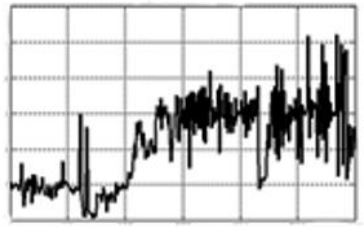
Predictive maintenance based on integration of statistics and autoencoder methods

Intelligent Business Optimizer Solution in a large paper manufacturing company

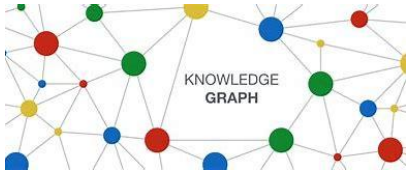
Business domain knowledge



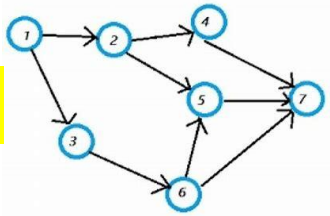
Business data



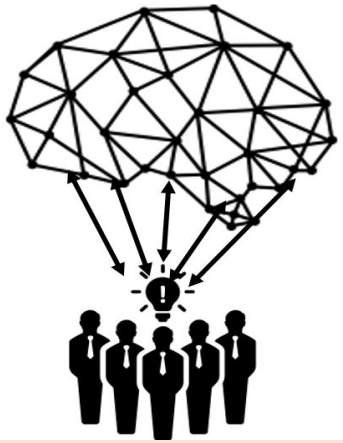
Knowledge graphs



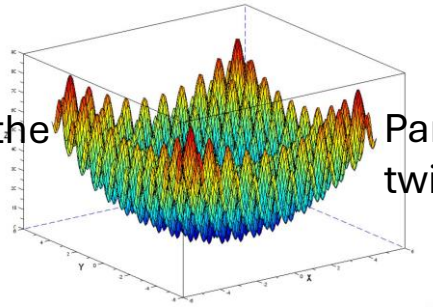
Causal models



Machine teaching



Digital brain of the Enterprise



Parallel digital twins

Intelligent Business Optimizer

Suggested optimal solution



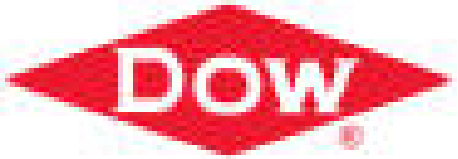
Pilot project: how the Digital Brain of the Enterprise could combine subject matter experts' tacit knowledge with production data to make more intelligent and automated decisions.

The pilot study showed a 10X increase in touchless processing of customer order throughput. The system fixed some order management errors that used to take days to resolve in seconds.

Key Lessons from 33 Years Applying AI

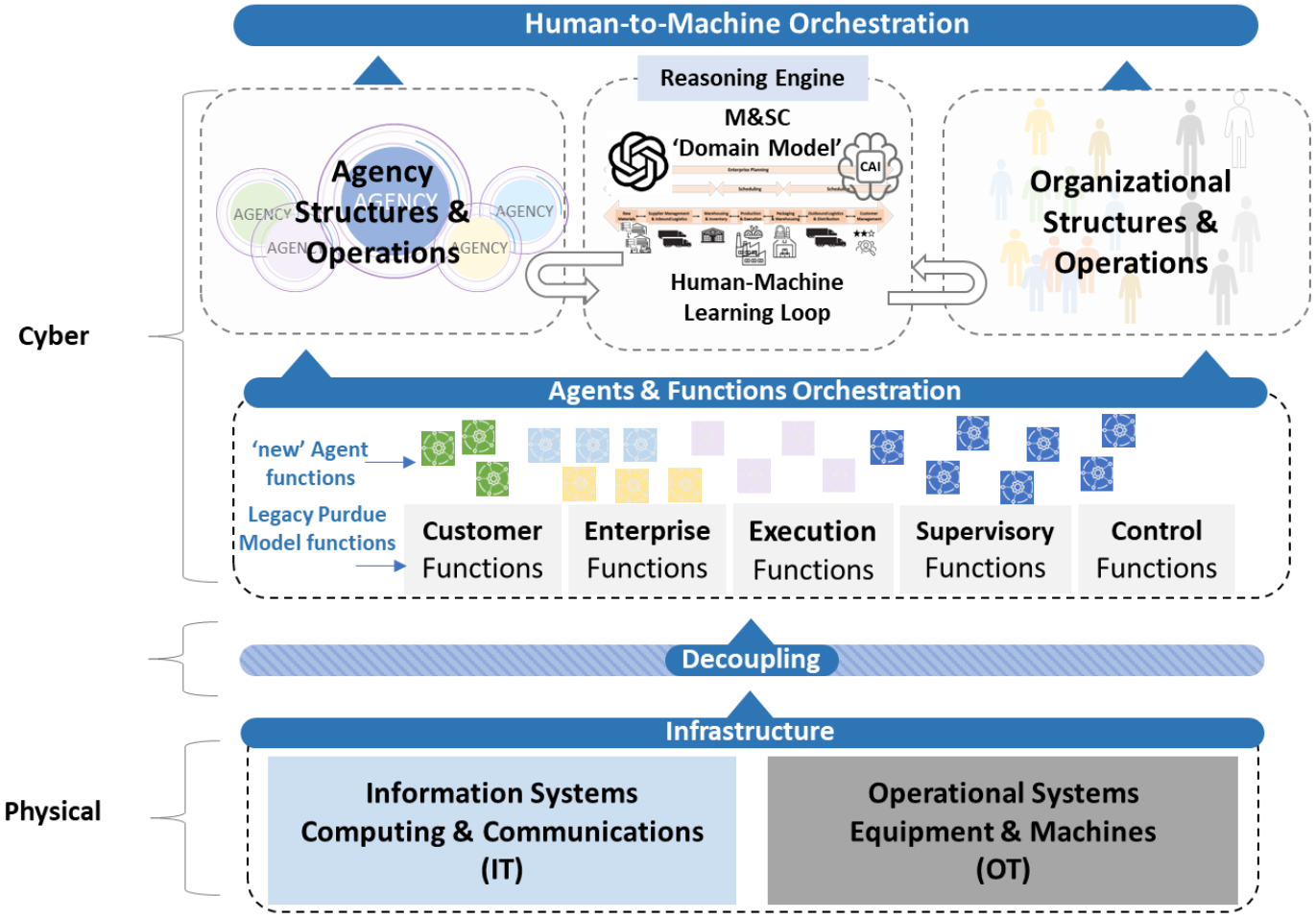
- **Top management vision and consistent support are ABSOLUTELY needed for the success of AI applications**
- **Technology is changing fast, but key business problems remain persistently the SAME**
- **Including employees who use AI applications in the development and sharing of benefits is KEY to acceptance**
- **Deep expert knowledge, scientific and engineering principles CANNOT be replaced by voodoo coding**







An Agentic AI Framework for Industrial Systems



Georgia-Pacific

The recommended framework for future business Agentic AI applications is based on optimal orchestration between humans and agents, NOT on autonomous agentic control of the Enterprise

The 10x AI engine for business productivity growth opportunity



Investment compartment

AI-driven automatic code generation

Agentic AI universal capability

GenAI mass-scale potential market

