SILO II

Stochastical Immunological Layer Optimizer

TRANSITION TECHNOLOGIES

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Stochastical Immunological Layer Optimizer

Bio-inspired computing is a field which helps us solve complex problems using computational methods observed in nature. For example, Artificial Intelligence algorithms and models such as Neural Networks, Genetic Algorithms and Particle Swarm Optimization, are very useful in industrial process control and optimization. One of the newest fields in bio-inspired computing are methods inspired by the operation of immune systems of living creatures. Characteristic features of Artificial Immune Systems are on-line learning and effective adaptation. These features are much desired in solutions which perform on-line industrial process optimization and control. Below we present SILO II - a new immune inspired optimizer of industrial processes, which has demonstrated with stunning success to provide high efficiency gains in power plants in USA, South Korea, Taiwan and Poland.

SILO II is one of the Emerson SmartProcess application modules used in large-scale industrial processes for advanced control and optimization. The main application of the SILO II system is combustion process optimization. Heat and electricity producers can minimize NO_X, CO and SO_2 emissions and increase generation efficiency. SILO II also can be used to increase plant controllability. Therefore, costs related to the power generation process itself, and to emissions control regulations are reduced. Furthermore, when using SILO II, companies may avoid the higher costs of emission mitigation systems allowing for substantial increases in their infrastructure efficiency. SILO II could also be used for FGD, SCR and SNCR optimization.

SILO II base information

SILO II system performs an on-line optimization of MIMO (Multi Input Multi Output) industrial processes. It is responsible for:

- **Maximization of income** that is related with output product,
- **Minimization of costs** which are related with fuel costs and penalties for air pollution.

The SILO II economical calculation module helps to define optimization goals, that assure the best economical profits. In the case of combustion processes in power boilers, SILO II increases process efficiency, reduces NO_X, CO and SO_2 emissions, reduces LOI (Loss of Ignition) and decreases unit heat rate.

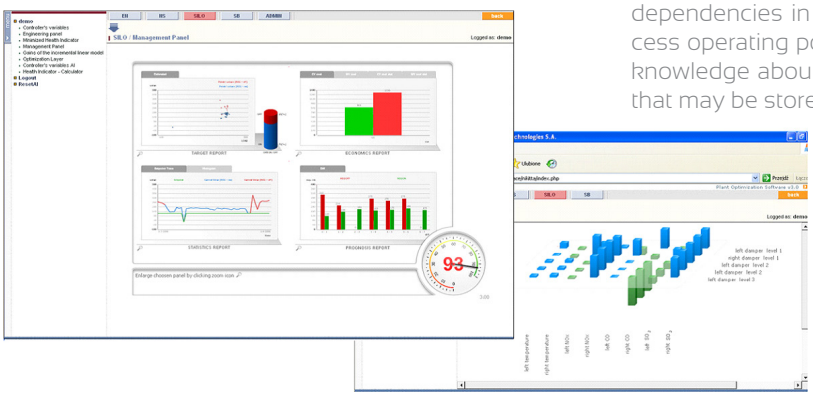


Fig. 1 SILO II web interface

SILO II is a completely new solution for industrial process optimization. This new approach is based on analogy with the immune systems of living creatures. Other advanced process control and optimization solutions are based on a large, sophisticated models, that are difficult to obtain, maintain and tune. SILO II uses a different approach. It gathers portions of knowledge (B cells) about the process, and uses selected portions of knowledge to forecast plant behavior in the close neighborhood of the current process operating point. Such an approach used within the SILO II system has some unique features:

On-line learning of a process based on current measurements

Comment: SILO II learns static process responses for a given control change. In particular it stores packets of information which in analogy to the immune system are like B cells. These packets are used by the optimization module to create a direct model of inner process dependencies in the neighborhood of the current process operating point. Moreover SILO II is able to gather knowledge about the process based on historical data that may be stored within a DCS system.

Direct and fast adaptation to current process state

Comment: Using its own knowledge base, SILO II is able to identify dependences between process inputs and outputs for each analyzed process operating point. It is a brand new approach in process non-linearity handling. Based on the B cell specialized knowledge, that represents process behavior in the neighborhood of current operating point, SILO II is also able to automatically create a mathematical model in every optimization period (e.g. every 5 minutes). It assures more direct adaptation to a non-linear characteristic in comparison with other solutions, which use manually created models.

Direct and fast adaptation to non-stationary process characteristics

Comment: Characteristics of industrial processes are changing over different time scales, ranging from days to months. These changes result from the wearing down or failure of devices, changes in chemical properties of components used in a process (e.g. fuel properties), unit modernizations or external condition changes (e.g. seasonality). SILO II is able to handle these changes via the continuous on-line learning of a process.

In SILO II there is no need for manual model creation process

Comment: In this case there is no need to perform long lasting and labor consuming identification experiments. SILO II learns the process in on-line mode and increases its efficiency over time (please refer fig. 2). At the beginning, after a SILO II installation, it has no knowledge about the process. SILO II uses a special heuristic to optimize the process and learns the basic process dependences. After a few hours it can start to create models. The accuracy of these models continually improves over time so that after one week, the solution can perform an efficient optimization of a process. What are the benefits to the user?

- There is no need to change the production schedule of a plant with long-lasting parametric tests. Thus avoiding significant loses for changes in production plan.
- There are no significant inefficiencies related to process operation with parametric tests. Long-lasting parametric tests can cause significant loses for a plant because process operation was dictated by testing requirements. This is also avoided with SILO II.
- The cost of implementation is significantly reduced, so there is a higher return of income for the customer.

One can see that SILO II significantly reduces customer loses related with manual model creation process.

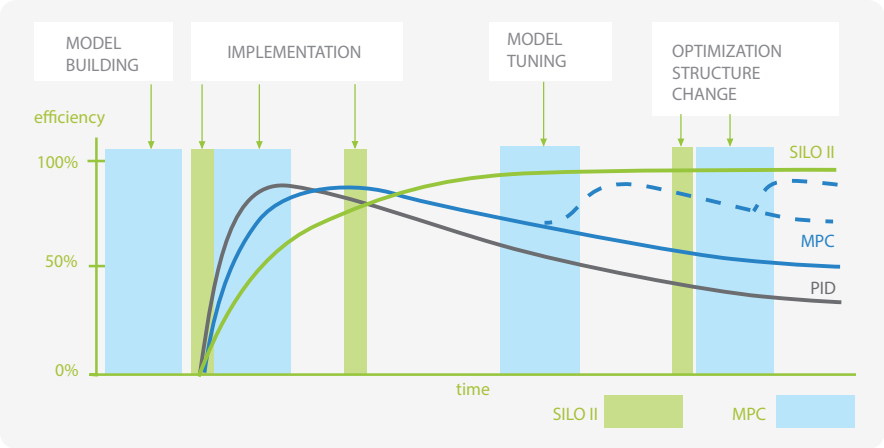


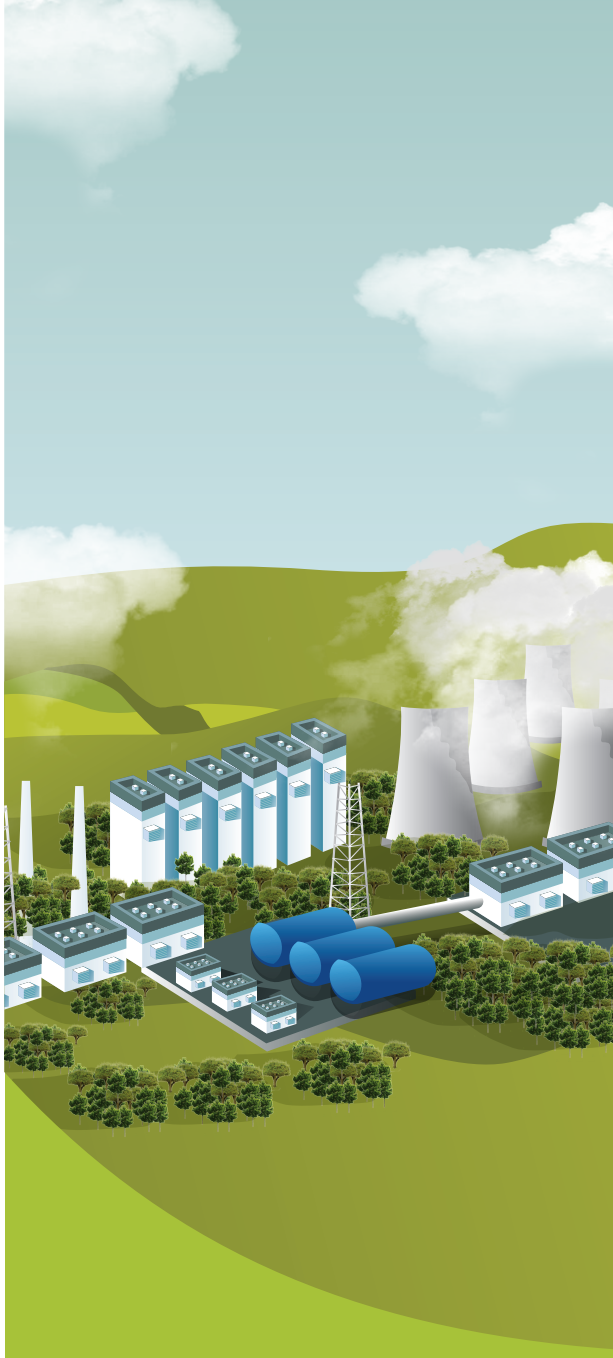
Fig. 2 Solution efficiency

There is no need for tuning SILO II models and, moreover, the cost related with tuning of the base control structure is decreased

Comment: There is no need for additional SILO II tuning, thanks to a very efficient adaptation mechanism. Over time SILO II can compensate for poor performance of the base control structure that is related to poor adaptation. It reduces the customer cost related with some base control structures tuning.

Optimization algorithm depends not only on the current process state but also on SILO II knowledge about the process

Comment: SILO II has Artificial Intelligence mechanisms to choose the best optimization strategy. SILO II uses the newest portion of knowledge (the newest B cells) that is related to the current process operating point to create a process model in the neighborhood of a current process state. If there is not enough knowledge that fits the current process operating point, SILO II tries to build a model that is based on stored knowledge from different operating points. If such knowledge is insufficient, SILO II searches for a better solution based on a special stochastic heuristic. At the same time SILO II gathers knowledge about the current process operating point, so this allows the process knowledge to become more and more accurate. Other solutions are not able to evaluate the quality of its knowledge base and are limited by the rigidity in the model.



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Easy modification of optimization task

Comment: Adding or removing control inputs, process outputs and measured disturbances to or from the SILO II structure is very easy. There is no need for additional parametric tests. SILO II will learn the new structure on the fly, which is of great benefits to the customer. Easy modification of the optimization structure provides higher flexibility in the plant modernization and development.

Easy modification of optimization goal

Comment: Based on a special cost and incomes simulator, users can change the optimization goals without stopping the optimization. The definition of performance indicator consists of a linear and a square part, thus the customer has higher flexibility in defining optimization goals.

Easy SILO II management based on WWW interface

Comment: SILO II Graphical User Interface is based on WWW technology. All users which are connected to intranet can have access to the SILO II interface.

Support for management, engineers and operators

Comment: Based on special SILO II modules, plant management can evaluate economical benefits of SILO II operation. Engineers can evaluate SILO II performance and read different kinds of statistical analysis. Operators can find an answer for the following questions: "Why SILO II has performed a particular operation?" and "What should I do to increase process performance?".

Fleet optimization solution

Comment: SILO II is dedicated for different types of large-scale plants. In case of combustion process optimization, it can handle all types of energetic boilers, different fuels and different load profiles. SILO II reaches highest performance during steady-state control, however there is a special dedicated mechanism that is activated during a transition state. Thanks to this mechanism, SILO II is able to handle operating point transitions (e.g. load changes). The SILO II optimizer is very easy to install and maintain. It has an efficient adaptation mechanism and a flexible structure of the optimization task, thus it can follow changes of process characteristics and modifications of production strategy. All these features make SILO II a perfect solution for a fleet optimization approach.

Possibility of expert knowledge implementation

Comment: There is a possibility to implement an expert knowledge about the process, even if such knowledge is fuzzy. Users can define constraints for chosen gains of an automatically created plant model.

SILO II - ZOLO BOSS integration

Comment: SILO II can be integrated with ZOLO BOSS measurements. The ZOLO BOSS is a new technology of measurement. It uses tunable diode laser absorption spectroscopy to measure temperature, O_2, CO, CO_2, H_2O across the furnace. The ZOLO BOSS consists of set of lasers placed at different furnace elevations. A set of ZOLO BOSS lasers from a single elevation creates a grid representing two-dimensional map of combustion process parameters. SILO II is able to read ZOLO BOSS measurements and use them to control a 3D shape of the fireball. SILO II controls the fireball's parameters such as: horizontal and vertical shift, angle, intensity and concentration, in order to optimize efficiency and emissions.

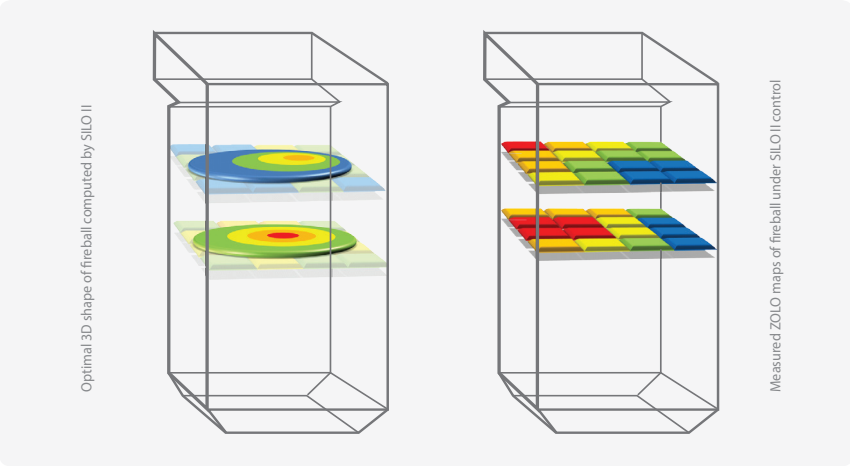


Fig. 3 SILO II - ZOLO BOSS integration

SILO II is a part of wide family of SmartProcess products related with process optimization, control and monitoring. It can be easily connected to the EDS system (Enterprise Data Server). In such a configuration, SILO II can utilize features from EDS such as:

- reporting,
- monitoring,
- long-term archiving,
- customized operator diagrams.

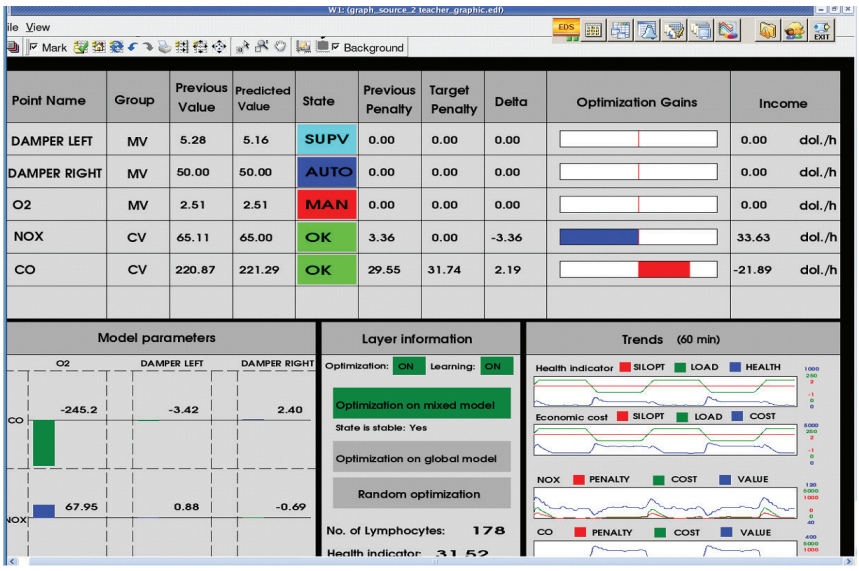


Fig. 4 SILO II diagram in EDS system

SILO II – how does it work?

The optimization of power boilers is an important topic in research and in the implementation of projects in the power industry. The combustion process in a power boiler is a complex process, with a large number of control variables, disturbances and outputs. This is a dynamic non-linear process characterized by long response time caused by process inertia and transport delay. It is hard to control such a process using only standard SISO (Single Input Single Output) control algorithms.

The task of SILO II is to perform an on-line optimization of the current process operating point. The optimizer is implemented above the base control layer in a layered control structure (refer fig. 5). The SILO II system calculates setpoints or setpoints corrections for controllers that operate in the base control layer. Control systems of power units in power plants are based on PI (Proportional-Integral) controllers. These controllers control sub-processes (e.g. oxygen level in exhaust gases or windbox to furnace differential pressure in the case of a power unit control system) that have an influence on a main optimized MIMO (Multi Input Multi Output) process (e.g. combustion process in the case of a power unit control system).
In our description the following terminology will be used:

- y - main process outputs vector (combustion process example: NO_x and CO emission, steam temperatures, output gases temperature, loss of ignition and other factors related with unit efficiency),
- d - main process disturbances vector (combustion process example: unit load, coal mill configuration, measured or estimated fuel calorific value, etc.),
- m^d - decision vector - setpoints for low level controllers (combustion process example: oxygen setpoint, auxiliary air dampers positions demand, OFA dampers positions demand, OFA tilts demand, burner tilts demand, coal feeder demand, FD and ID fan balance corrections, correction of windbox to furnace differential pressure setpoint, etc.),
- m^t - traced setpoints for low level controllers (combustion process example: oxygen setpoint that enters the PI controller in DCS system, demand signal that is sent to OFA dampers, etc.),
- m^c - vector of measured sub-process outputs - inputs to the main optimized process (combustion process example: measured oxygen content in flue gases, measured OFA position, etc.),
- m^f - control variables availability vector (combustion process example: status of the oxygen control loop - SILO II supervisory enabled/disabled, etc.),
- m^p - operator setpoints vector (combustion process example: operator demand for oxygen, etc.).

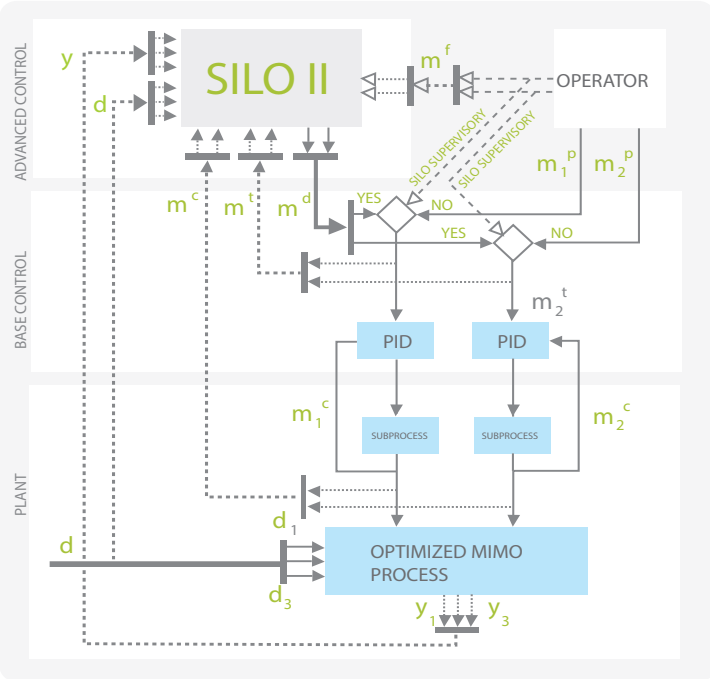


Fig. 5. SILO II system in a layered control structure. Description: y - main process outputs vector, d - main process disturbances vector, m^d - decision vector (setpoints for low level controllers), m^t - traced setpoints for low level controllers, m^c - vector of measured sub-process outputs (inputs to the main optimized process), m^f - control variables availability vector, m^p - operator setpoints vector.

ANALOGY BETWEEN IMMUNE SYSTEM AND SILO II.	
Immune System	SILO II
Pathogen	Measured and non-measured disturbances
B cell	A data unit that represents a static process response for a control change in a particular process operating point
Antibody: antigen binding side	Current process operating point
Antibody: effector part	Optimal control vector change Δm^d
T_h cell	Algorithm which is responsible for selection of proper group of B cells during model creation process
Secondary immune response	Mixed Model Optimization algorithm
Primary immune response	Quasi-Random Extremum Control layer of the optimization algorithm

The SILO II system optimizes a process steady state. The output decision vector m^d is updated every optimization cycle period T_{opt}. This time period is not shorter than the time needed to reach a new process steady state after a control vector change (this time varies from 5 to 20 minutes in case of a combustion process optimization). Changes to the m^d vector (setpoints for base controllers) are limited due to the stable and safe operation of the base control system. In the case of detecting a significant process operating point transition (e.g., essential modification of an industrial plant load), the SILO II system activates a transition state mechanism.

In such a case, SILO II tries to move the decision vector m^d to the neighborhood of an optimal solution related to the new process operating point. This m^d vector transition is safe for the plant and fast in comparison with standard steady state optimization. In each optimization cycle the SILO II system calculates the decision vector increment Δm^d based on:

- measured output vector y,
- measured disturbances vector d that have an impact on the optimized process outputs,
- information about availability of control loops and devices (m^f vector) that can be influenced by SILO II.

The optimizer calculates an output vector increment Δm^d and adds this increment to the vector m^t that represents traced decision variables (traced setpoints for low level controllers). The calculated sum of Δm^d and m^t is saved in the output m^d vector. Utilization of the m^t vector is caused by application of rate and range constraints for setpoints in the base control layer. If the k-th low-level control loop is excluded from SILO II supervisory (m^f_k = 0) then SILO II passes the m^t_k value directly to the m^d_k output element. Thus inactive outputs trace operator settings. It allows smooth switching between SILO II and process operator.

Engineers about SILO II...

The Joppa station runs year round with the Smartprocess® Combustion Optimizer and realizes an average 9% NO_x reduction, improved CO control, and more stable steam temperature.

Larry Lepovitz
Systems Engineer
Electric Energy, Inc.
Joppa Station

Biological inspiration

The SILO II operation and optimizer structure are inspired by immune system – biological structures and processes within an organism. Analogy between immune system and SILO II table (page 5) in order to provide information concerning biological inspiration of our system.

In SILO II system there are two main, independent modules: the Optimization and the Knowledge Gathering module. The optimization module uses the collected knowledge to find such control vector change (Δm^d) that minimizes the following performance indicator:

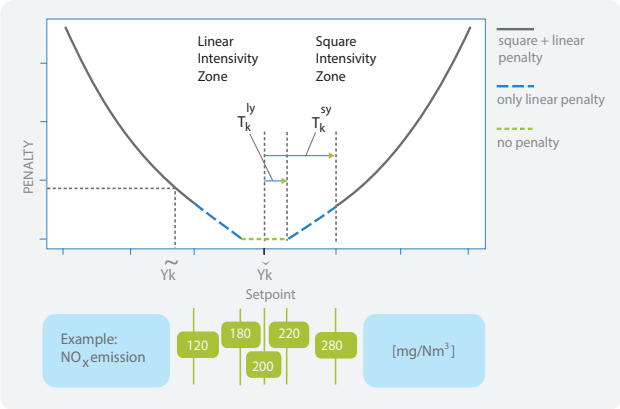


Fig. 6. Penalty function for one output signal (e.g. NO_x emission).

$$J = \sum_{k=1}^{n_m} \left[\alpha_k \left(|\check{m}_k^c - \tilde{m}_k^c| - \tau_k^{lm} \right)_+ + \beta_k \left(\left(|\check{m}_k^c - \tilde{m}_k^c| - \tau_k^{sm} \right)_+ \right)^2 \right] + \sum_{k=1}^{n_y} \left[\gamma_k \left(|\check{y}_k - \tilde{y}_k| - \tau_k^{ly} \right)_+ + \delta_k \left(\left(|\check{y}_k - \tilde{y}_k| - \tau_k^{sy} \right)_+ \right)^2 \right]$$

α_k linear penalty coefficien for k-th control variable,
β_k square penalty coefficient for k-th control variable,
γ_k linear penalty coefficient for k-th optimized output,
δ_k square penalty coefficient for k-th optimized output,
τ_k^{lm} width of insensitivity zone for linear part of penalty for k-th control variable,
τ_k^{sm} width of insensitivity zone for square part of penalty for k-th control variable,
τ_k^{ly} width of insensitivity zone for linear part of penalty for k-th output,
τ_k^{sy} width of insensitivity zone for square part of penalty for k-th output,
$(\cdot)_+$ "positive part" operator $(x)_+ = \frac{1}{2}(x + |x|)$
$\tilde{m}_k^c$ current process value for k-th control variable,
$\tilde{y}_k$ current process value for k-th optimized output,
$\check{m}_k^c$ demand value for k-th control variable,
$\check{y}_k$ demand value for k-th optimized output.

The optimized performance indicator is the sum of penalties related to the process outputs and selected elements of the m^c vector. The SILO II system penalizes a difference between a demand value of a process output $\check{y}_k$ (optionally for a selected element of the $\check{m}^c$ vector) and the measured or estimated value for output $\tilde{y}^k$ (optionally a selected element of the $\tilde{m}^c$ vector). Each single penalty is the sum of a linear and square term, and each term takes insensitivity zones into account. No penalty is applied when an analyzed signal is within an insensitivity zone. Penalty for one output signal is presented in fig. 6.

Gathering knowledge about a plant

The goals of the SILO II Knowledge Gathering module are listed below:

- Identification of the static relations between optimized process inputs m^c (measured input to a main, optimized process) and outputs y at different process operating points;
- Saving and updating of long term averages of the control vector m^c at different process operating points (e.g. different power unit loads and coal mill configurations in the case of a power boiler optimization). This information will be used to handle a significant process point transition in a safe and effective way.

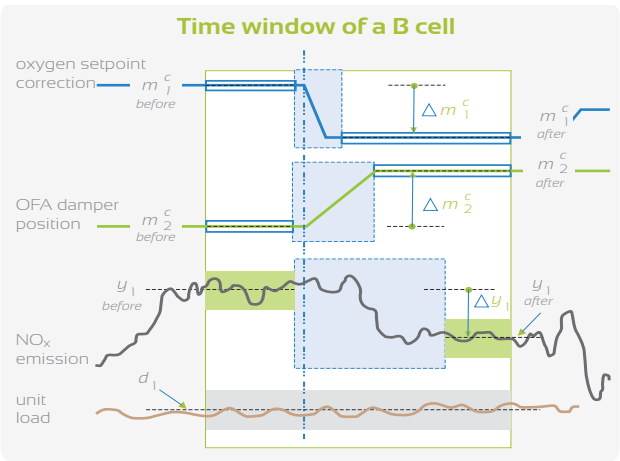


Fig.7. Simplified example of a time window of a B cell

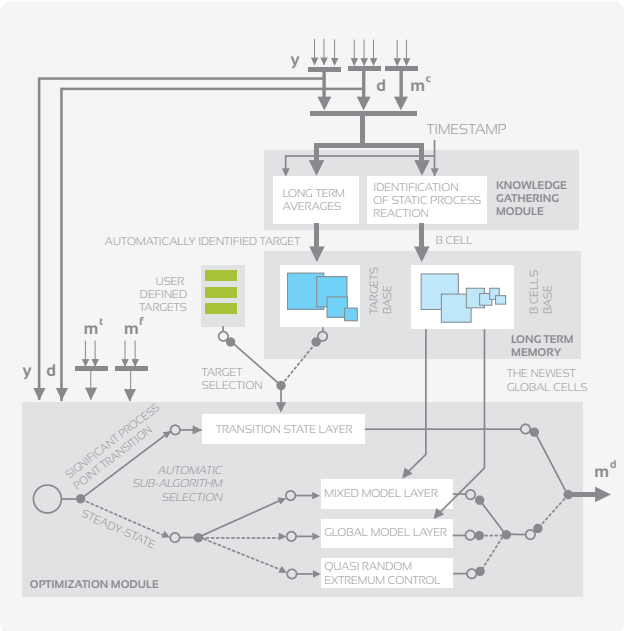


Fig. 8. Optimization and Knowledge Gathering module.

Identification of the static relations between process inputs and outputs is based on an on-line analysis of a time window. This time window consists of the current and historical values of the y, d and m^c vectors (refer fig. 7) . The Knowledge Gathering module only analyzes time windows that include an essential change of at least one element of the vector m^c and in which the process disturbances d are constant. Static process reaction for a control change is automatically identified. The computed increments Δy and Δm^c, and information about the current process operating point, are saved in memory in the form of a B cell (refer fig. 8). Each B cell has a timestamp. Immune memory in a real SILO II implementation for combustion process optimization in a power plant, consists of tens of thousands of B cells.

The information stored in B cells is utilized in the model creation process which is automatically performed in each optimization cycle.
The second goal of the Knowledge Gathering module is the saving and updating of long term averages of the m^c, d and y vectors at different process operating points. These long term averages are transformed into AIT (Automatically Identified Targets) objects that are used in the *Transition State* layer (a sub-algorithm of the Optimization module). Each AIT has a timestamp. When a process transition state is detected, the system searches for the most recent AIT that fits the current or estimated process operating point.

Optimization module: Quasi Random Extremum Control

In the initial phase of SILO II operation the size of the immune memory is relatively small. In analogy to the immune system one can say that the body is often attacked by new, unknown pathogens. Early on, SILO II does not have sufficient knowledge to create a mathematical model of the process and solve the optimization task based on this model. A special heuristic that is applied in the *Quasi Random Extremum Control* layer covers the following goals:

- Gathering knowledge about the process. This is done by modifying the m^d vector in such way that each modification can be treated as a standard identification experiment. New B cells are created based on these identification experiments;
- Decreasing the value of an optimized quality indicator at a long time horizon with the assumption that process disturbances are constant at a long time horizon. In analogy to the immune system one can say that a goal of the *Quasi Random Extremum Control* layer is the elimination of the pathogen at the long time horizon with the assumption that the body is attacked by one sort of pathogen at the long time horizon (a primary immune response);
- Maintaining the good conditioning of the model identification task.

A special heuristic applied in the *Quasi Random Extremum Control* layer changes only one element of the m^d vector in each optimization cycle (e.g., only the oxygen setpoint is changed in case of a combustion process). In reaction to this change, the process outputs y reach a new steady state. The Knowledge Gathering module automatically identifies such a static process reaction and creates a B cell. In a new optimization cycle a different element of m^d (e.g. OFA damper position demand) is modified and a new B cell is created. After a defined number of cycles, the best m^d vector value is restored and applied. This value of the m^d vector is related to the lowest registered value of an optimized quality indicator.
The Quasi Random Extremum Control layer is executed if:

- There are not enough B cells in the immune memory to create a mathematical model of the process;
- The knowledge stored in the immune memory is not sufficient to improve the value of the performance indicator. It means that the model is not accurate enough. The applied increment of the m^d vector calculated in the *Mixed Model Optimization*, or the *Global Model Optimization* layer (refer fig. 8), is not able to decrease the value of the quality indicator.

Optimization module: Steady State Optimalization

Steady state model based optimization is performed in the *Mixed Model Optimization* or the *Global Model Optimization* layer (refer fig. 8). In both layers a model is formulated in the following way:

$$\Delta y = \Delta m^d K$$

In the case of mixed model based optimization, elements of the matrix K (process gains) are estimated based on information stored in the local observation matrices ΔM_L and ΔY_L, as well as the global observation matrices ΔM_G and ΔY_G, where

$$\Delta M_L = \begin{bmatrix} \Delta m^c_{1,1} & \Delta m^c_{1,2} & \dots & \Delta m^c_{1,nm} \\ \Delta m^c_{2,1} & \Delta m^c_{2,2} & \dots & \Delta m^c_{2,nm} \\ \vdots & \vdots & \ddots & \vdots \\ \Delta m^c_{l,1} & \Delta m^c_{l,2} & \dots & \Delta m^c_{l,nm} \end{bmatrix},$$

$$\Delta Y_L = \begin{bmatrix} \Delta y_{1,1} & \Delta y_{1,2} & \dots & \Delta y_{1,ny} \\ \Delta y_{2,1} & \Delta y_{2,2} & \dots & \Delta y_{2,ny} \\ \vdots & \vdots & \ddots & \vdots \\ \Delta y_{l,1} & \Delta y_{l,2} & \dots & \Delta y_{l,ny} \end{bmatrix}.$$

Each of the l rows of the ΔM_L matrix consist of increments Δm^c_i of elements of the m^c vector. These increments are stored in a local B cell. This local B cell belongs to the set of l youngest local B cells. The local B cell is a selected B cell that is related to the current process operating point. Such a B cell was created when a historical process operating point (e.g. unit load in case of a combustion process optimization in a power boiler) was similar to the current process operating point. By analogy, the matrix ΔM_G consists of m^c vector increments that are stored in the set of g youngest global B cells. Global B cell selection is based only on a time criterion. Each of the l rows of the ΔY_L matrix consist of y vector element increments Δy_i that are stored in a local B cell. By analogy, the matrix ΔY_G consists of y vector increments that are stored in the set g youngest global B cells.
A vector k is related to a selected column of the process gains matrix K. It represents gains between process inputs and selected process output. In the case of a MISO (Multi Input Single Output) model, a special additional optimization task is executed in order to estimate a vector k value

$$\min_k \{ k^T(\eta \Delta M_L^T \Delta M_L + v \Delta M_G^T \Delta M_G) k - 2k^T(\eta \Delta M_L^T \Delta y_L + v \Delta M_G^T \Delta y_G) \}$$

with constraints

$$k^l \le k \le k^u$$

The presented additional optimization task, allows for the utilization of constraints related with automatically identified model gains. In most SILO II implementations these gains are unbounded. In such a case, a Least Square Method can be used to estimate elements of the gain matrix *K*. Thanks to the additional optimization task, the system can use some expert knowledge about the range of gain values for selected dependences between process inputs and outputs.
An optimal increment Δm^d of the m^d vector is computed based on the identified model. This increment minimizes the value of a quality indicator. It also fulfills constraints for a maximal absolute increment of the m^d vector in one optimization cycle. The following optimization task is solved in each optimization cycle:

$$\min_{\Delta m^d} \left\{ \sum_{k=1}^{n_m} \left[\alpha_k \left(\left| \check{m}_k^c + \Delta m^d - \tilde{m}_k^c \right| - \tau_k^{lm} \right) + \right.\right.$$

$$\left. + \beta_k \left(\left(\left| \check{m}_k^c + \Delta m^d - \tilde{m}_k^c \right| - \tau_k^{sm} \right)_+ \right)^2 \right] +$$

$$+ \sum_{k=1}^{n_y} \left[\gamma_k \left(\left| \check{y}_k + \Delta m^d K_k - \tilde{y}_k \right| - \tau_k^{ly} \right) + \right.$$

$$\left.\left. + \delta_k \left(\left(\left| \check{y}_k + \Delta m^d K_k - \tilde{y}_k \right| - \tau_k^{sy} \right)_+ \right)^2 \right] \right\}$$

with constraints

$$\Delta m_{low}^d \le \Delta m^d \le \Delta m_{hi}^d ,$$

$$m_{low}^d \le m^t + \Delta m^d \le m_{hi}^d$$

The computed increment Δm^d is added to the current value of the m^t vector. This sum is saved as the optimizer output m^d.

$$m^d = m^t + \Delta m^d$$

The increment of inactive elements of the m^d vector (defined by the m^f vector – refer fig. 5) is set to zero.
The *Mixed Model Optimization* layer is activated when SILO II has sufficient knowledge about static process dependencies in the close neighborhood of the current process operating point. If there are not enough local B cells in memory, then only global B cells will be used to create a global model. However if there are not enough global B cells in memory (initial phase of SILO II operation), or further improvement of a performance indicator value is not possible based on the model, then SILO II switches to the *Quasi Random Extremum Control* layer. By analogy to the immune system, the operation of the *Mixed Model Optimization* layer can be compared to a secondary immune response. The SILO II system uses the knowledge stored in the B cells to provide the fast and effective elimination of pathogens (process disturbances compensation).

Optimization module: Transition of Process Operating Point

The newest version of SILO II has a new algorithm that is able to handle a significant process transition in an effective way. This algorithm is implemented in the *Transition State* layer in the Optimization module of SILO II (refer fig. 8). In the case of a combustion process optimization, this new mechanism allows for optimization of relatively small power units characterized by frequent transitions of unit load.

The AIT (Automatically Identified Targets) and UDT (User Defined Targets) are used to move the control vector value to a point that lies in a close neighborhood of an optimal solution related with the new process operating point. This transition is fast. A new process operating point is a starting point for model based optimization.

SILO II post-implementation analysis in one of large power plants

Plant description

- 2 units
- Max. unit load is 650 MW
- Fuel: hard coal
- 6 levels of burners located in corners

Optimization goals (process outputs)

- Minimization of NO_x emission
- Keep CO emission below 400 PPM

Control variables (11 signals)

- Correction of O_2
- Correction of windbox to furnace differential pressure
- Average SOFA tilts set point for three top levels
- Average SOFA tilts set point for three bottom levels
- Correction of SOFA opening for three top levels
- Correction of SOFA opening for three bottom levels
- Difference between top and bottom SOFA opening's set point in top three levels
- Difference between top and bottom SOFA opening's set point in bottom three levels
- Feeder speed (x3)
-

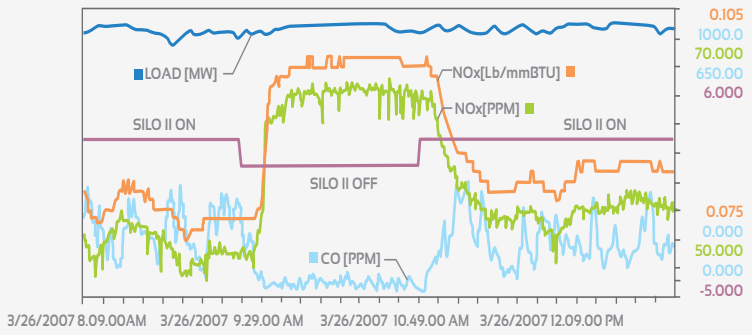
Disturbances: 9 signals

- Unit load
- Pulverizer configuration
- Burner tilts

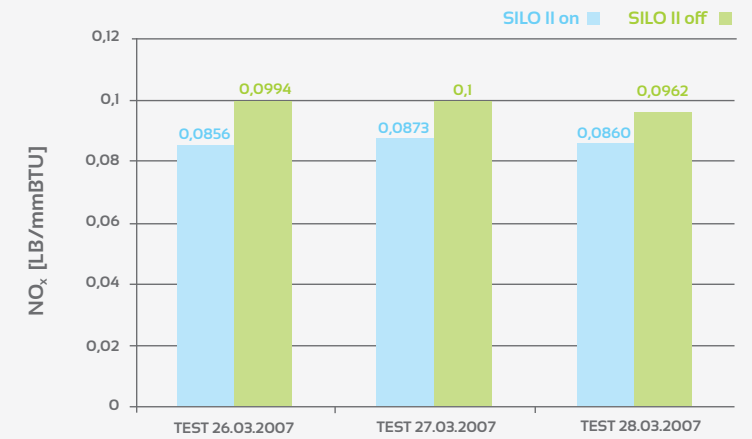
The optimization goals were realized: NO_x emission was **reduced by 12,4 %** and the CO emission was **below the limit (400 ppm)** all the time ▼

Results - unit 1

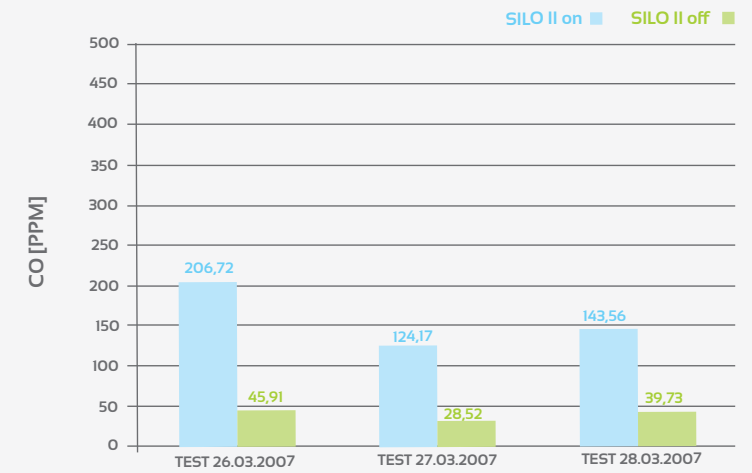
Trends



Summary



Average NO_x reduction - 12,4 % ▲



Average CO emission was below the limit (400 ppm) ▲

Main conclusion

Emission	Units	SILO II off	SILO II on
TEST I			
NO_x	LB/mmBTU	0.0994	0.0856
CO	ppm	45.91	206.72
TEST II			
NO_x	LB/mmBTU	0.1	0.0873
CO	ppm	28.52	124.17
TEST III			
NO_x	LB/mmBTU	0.0962	0.0860
CO	ppm	39.73	143.55

SILO II post-implementation analysis in one of mid-size power plants

Plant description
- 3 units
- Unit 1 – available unit load 221 MW
- Unit 2 – available unit load 200 MW
- Unit 3 – available unit load 226 MW
- Fuel: hard coal with wood chips
- 4 coal mills
- 24 burners: 6 burners in each of 4 levels
- OFA dampers

Primary goals:
- Keep NO_x emission (one hour average) below 500 mg/Nm^3
- Keep CO emission (5 minute average) below 250 mg/Nm^3

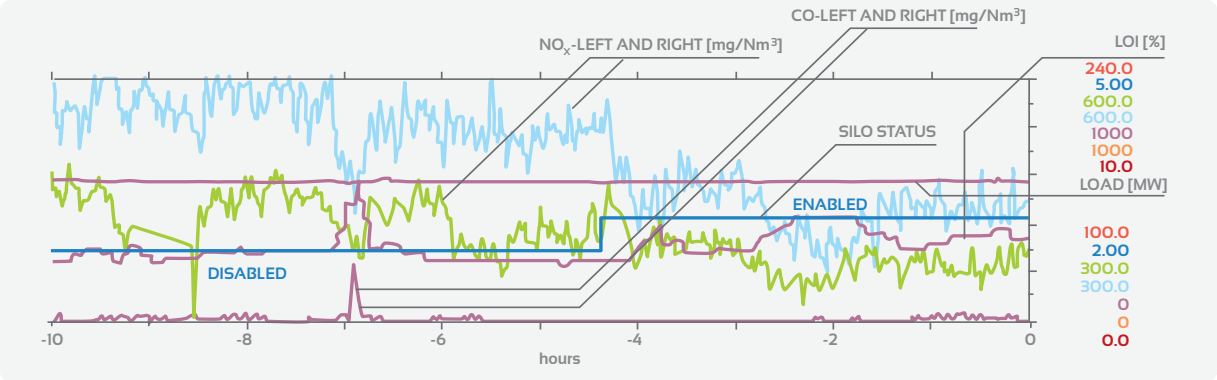
Secondary goals:
- Keep LOI below 5%
- Keep SH temperature on 540 °C
- Keep flue gas temperature below 140 °C (FGD requirement)

Outputs (9 signals)
- NO_x emission – left and right side
- CO emission – left and right side
- Estimated SH temperature - left and right side
- Flue gas temperature before precipitator – left and right side
- LOI

Control variables (11 signals)
- O_2 level setpoint
- Sec. air dampers (x8)
- OFA dampers (x2)

Disturbances (6 signals)
- Unit load
- Estimated coal BTU
- Status of each coal mill (x4)

Results



Main conclusion

	Units	SILO II off	SILO II on
Load range	MW	106.0-195.3	107.8-203.0
NO_x exceedence time	%	10.14	0.0
CO exceedence time	%	1.15	0.19
Average SH temp	°C	532.24	536.58
LOI exceedence time	%	59.0	24.14

The optimization goals were realized: the NO_x emission was **below the limit** (500 mg/Nm^3) all the time. CO exceedance time was **significantly reduced**. Average SH temperature was increased by 4°C. LOI exceedance time was **significantly reduced by 35%.**

SILO II has been implemented in 31 power units in power plants in the USA, South Korea, Taiwan and Poland. In each of these plants SILO II has essentially decreased NO_x emission, maintained CO emission below the limit and improved process efficiency.

Power Plants in USA:

Newton, unit 1	600 MW
Newton, unit 2	600 MW
Tampa, unit 3	400 MW
Nearman, unit 1	185 MW
Danscammer, unit 3	250 MW
Danscammer, unit 4	250 MW
Roxboro, unit 3	700 MW
Northport, unit 2	375 MW
JP Madgett, unit 6	380 MW
Wagner, unit 2	136 MW
Valley, unit 1	140 MW
Valley, unit 2	140 MW
Trimble County, unit 1	514 MW
Kapp, unit 2	218 MW
Amos, unit 3	816 MW
Escalante, unit 1	250 MW
Boardman, unit 1	550 MW
Genoa, unit 3	379 MW
Dry Fork, unit 1	440 MW
Leland Olds, unit 2	[in progress]
Prairie State, unit 1	[in progress]

Power Plants in Poland:

Ostroleka, unit 1	200 MW
Ostroleka, unit 2	200 MW
Ostroleka, unit 3	200 MW
Polaniec, unit 1	200 MW
Polaniec, unit 4	200 MW
Polaniec, unit 8	200 MW

Power Plants in Taiwan:

Taichung, unit 8	550 MW
Taichung, unit 5	550 MW
Taichung, unit 7	550 MW
Taichung, unit 6	550 MW

Power Plants in South Korea:

Young Hung Do, unit 3	890 MW
Young Hung Do, unit 4	890 MW

Awards

SILO II is protected by patents in USA, China, India and Poland. SILO II has received the following awards:

- Silver medal at International Exhibition "Innovations, Research and New Technologies - INNOVA 2006", Brussels, 2006
- Diploma from Polish Ministry of Science at Polish Research Exhibition, Warsaw 2007
- Product of the Year 2007 by Control Engineering magazine, Warsaw 2007
- Polish Product of the Future 2008 by Polish Agency for Enterprise Development

Scientific Publications

SILO II system was described in 14 scientific publications. Selected publications are presented below:

[1] K. Wojdan, K. Świrski, M. Warchol, G. Jarmoszewicz, T. Chomiak: „Bio-inspired process control", book chapter "Bio-inspired computing and communication networks" edited by Yang Xiao, CRC Press – Taylor and Francis Group, ISBN 978-1-4200-8032-2, Boca Raton, USA, March 2011

[2] K. Wojdan, K. Świrski, M. Warchol, J. Milewski, A. Miller: "A Practical Approach To Combustion Process Optimization Using an Improved Immune Optimizer", Sustainable Research and Innovation Proceedings, vol. 3, Kenya, 2011

[3] K. Wojdan, K. Świrski, and M. Warchol: "Transition State Layer in the Immune Inspired Optimizer", Trends in Applied Artificial Intelligence, Lecture Notes in Artificial Intelligence, vol. 6096, pp. 11–20, 2010

[4] K. Wojdan, K. Świrski, M. Warchoł, M. Maciorowski: "Conditioning of Model Identification Task in Immune Inspired Optimizer SILO", book chapter "IAENG Transactions on Engineering Technologies Volume 3", American Institute of Physics (AIP), November 2009

About Transition Technologies

Since over 20 years we have been providing our customers with the highest world's level IT solutions based on the latest tech nologies. Our offer includes:

- Development and distribution of software for utility sectors
- Optimization of technological processes
- Electrical energy and gas trading
- Risk management
- Programming
- Engineering services
- Solutions to mobile technologies
- Research and development projects
- Software service outsourcing
- Software consulting

Our established technological leadership is an outcome of a long-term experience in advanced projects implementation and application of the most innovative solutions, which together have resulted in a number of competitive realizations adjusted to the customers' needs.
We believe that our employees are the key to our success. Our team consists of exceptionally educated young people – graduates of major polish technical universities. Their knowledge and professional consultancy in application of delivered solutions determine the quality and innovation of our products. With offices located in five Polish cities; Warsaw, Lodz, Bialystok, Wroclaw and Ostrow Wielkopolski in Germany and in United States our company maintains rapid and dynamic growth.

TRANSITION TECHNOLOGIES

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