# Immune Inspired System for Chemical Process Optimization using the example of a Combustion Process in a Power Boiler

K. Wojdan, K. Świrski, T.Chomiak

***Abstract*—The article presents an optimization method of combustion process in a power boiler. Immune Inspired Optimizer SILO is used to minimize CO and NOx emission. This solution is implemented in each of three units of Ostroleka Power Plant (Poland) and in the Newton Power Plant (USA). The result from the second SILO implementation in Newton Power Plant is presented. The results confirm that this solution is effective and usable in practice and it can be a good alternative to MPC controllers.**

## I. Introduction

The optimization of power boilers is one of the most common topics in research and in implementation projects in energetic industry applications. The large number of power plants, the complex problems of their optimization and significant economic impact results in this topic being discussed in many scientific papers and articles ([1]-[4])

The energetic boiler is a complex installation, with a large number of control variables. The combustion process in a power boiler is a dynamic non-linear process characterized by long response time, cased by process inertia and transport delay. It is hard to control such a process using only classical control algorithms (i.e.: PID controllers [5]).

In this article we present SILO – a new method of combustion process optimization, inspired by the immune system of living creatures. The main features of the presented solution are:

- continuous learning and adaptation
- low implementation cost (in comparison to MPC controllers)

NOx and CO emission reduction, raising of the boiler efficiency and steam temperatures symmetrization are the typical goals in combustion process optimization. A diagram of a power boiler and the control signals, disturbance signals and process outputs forming its combustion process control is shown in Fig. 1.

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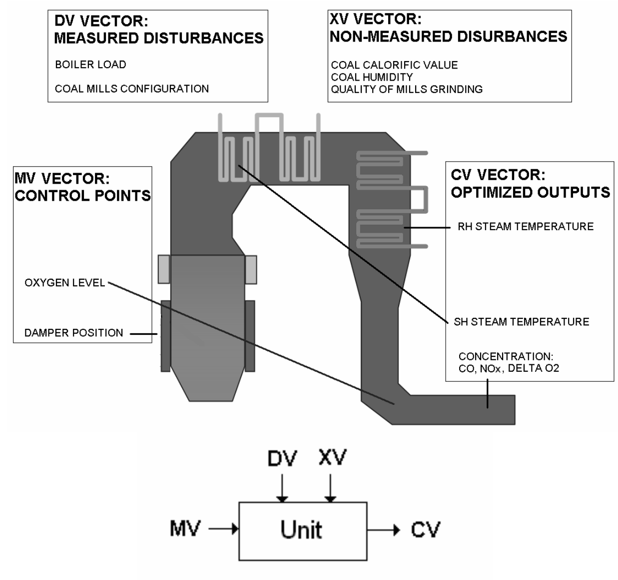



Fig. 1. Diagram of a power boiler and its signals.

## II. MPC Approach

MPC controllers are a well proven solution to combustion process optimization problems. The optimization algorithm in a MPC controller is based on a dynamic model of the combustion process. The optimal control vector is the control vector in consecutive moments *MV(i),MV(i+1),...,MV(i+L-1)* which minimize difference between estimated process's outputs and demand output values in consecutive moments. Moreover an optimized quality indicator includes a penalty for a control signals values change, which ensures lower energy consumption and lower device wear. For more information about MPC controllers please refer to [6]-[9].

The implementation of optimizations systems has been undertaken by several companies - NeuCO (USA), Pavillion (USA), Pegasus (USA), Transition Technologies (Poland). Most of the implementations bring positive results. Usually NOx emission is reduced by 10-30 % (there are different results on different types of boilers and on different boiler's load range). Boiler efficiency is improved by 0.1-0.8 % (lower oxygen level in exhaust fumes, lower CO emission and lower exhaust fumes temperature). Below we present some results from the installation of MPC controllers performed by Transition Technologies company in cooperation with Emerson Process Management.

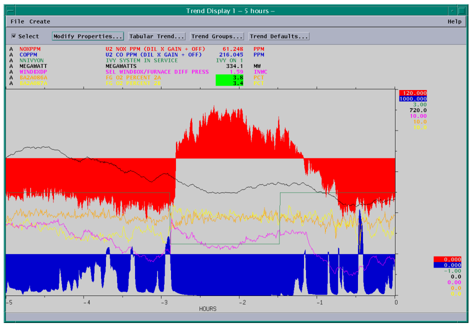


Fig. 2. Typical results for 650 MW unit with corner burners (Ameren's Power Plant, USA, 2002), trend graphic in control system; red color – NOx emission showing optimization system enabled and disabled (horizontal line shows emission limit); blue color -CO emission.

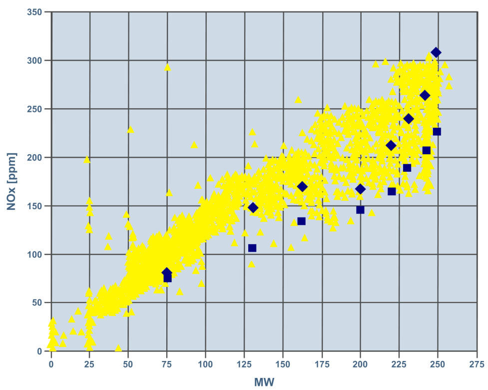



Fig. 3. Long term confirmation of NOx minimization results (6 month summary – 275 MW unit in Joppa Power Plant in USA. yellow triangles – NOx emmision before modernization, blue rhombus – after tuning classic control systems, blue squares – results after MPC controller installation)

In spite of the numerous advantages of MPC controllers, this approach has two basic disadvantages:

- Implementation of MPC controller is expensive. Engineers have to have precise knowledge about the combustion process to create a dynamic mathematical model. In practice engineers have to perform long-lasting and labour-consuming parametric tests. While computer cost is low, the cost of the highly qualified engineers is a significant load for power plant budget. Moreover some test scenarios can cause the boiler to work inefficiently. In some types of plants, there is no possibility to perform tests on all boiler configurations.
- Dynamic model has to be periodically updated because of changes in the characteristics of boiler devices or a change in fuel parameters.

There is no possibility to eliminate those disadvantages using standard methods. This motivates us to search for new techniques. It seems that the SILO system, which is a stochastic optimizer inspired by artificial immune system theory, is a good method to solve such problem.

## III. Biological and Artificial Immune Systems

Dąbrowski in [10] noticed, that immune system, like the nervous system, is a particular structure, which is able to gather and develop skills during learning and testing process. Moreover this system has memory. It can develop new or lost old abilities, according to external conditions. The immune system's features mentioned by Dąbrowski come in useful when solving diverse technical problems.

The main goal of the immune system is to protect organism against the pathogens. The term pathogens means viruses, bacteria, parasites and other microorganisms, which are dangerous for the living organism. Therefore the immune system has to properly detect and effectively eliminate pathogens. Pathogens have antigens, which induce an immune response. Antigens are detected by detectors – lymphocytes, whose structure represents directly the knowledge of the immune system. There are two types of lymphocytes in the immune system - B cells and T cells. In our article we will concentrate on the B cells and Th cells (sub-group of T cells). Each B cell could have a different combination of tools to destroy pathogens. Thus lymphocytes could have varying levels of effectiveness in fighting with particular sort of pathogens. Indeed those tools are the antibodies, which are produced by B cells ([11] - [13]). New B cells are created in bone marrow without the stimulation of antigens or during the clonal selection process, when they are created by antigen stimulation [13].

Continuous learning is a characteristic feature of the immune system. This process is connected with the so-called primary response ([11], [14]). It's the organism's reaction to new, unknown pathogen. The primary response of the immune system is usually slow. The system needs time to eliminate an unknown pathogen. It should be noticed that information about a pathogen is remembered after a successful defense action. It causes the organism's reaction to be faster and more effective to a pathogen's renewed attack. It is a secondary response ([11], [14]) which testifies to the adaptability of the immune system.

Nowadays knowledge about the immune system is the base for artificial immune systems theory. This theory inspires the construction of efficient information processing systems, which are able to learn continuously and adapt to new environments.

## IV. Problem representation

In this chapter the representation of the combustion process optimization problem in the context of immune systems will be described. The structure of the immune inspired optimizer SILO will be compared with the real immune system.

### *A. Pathogen*

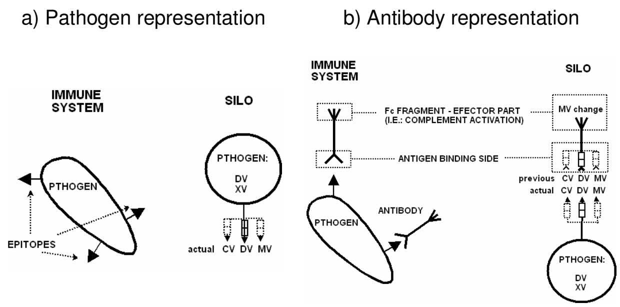



Fig. 4. Pathogen and antibody representation.

The pathogen represents the disturbances (measured and non-measured), which effect the work of the boiler. In some points this approach is similar to the idea of Krishnakumar and Neidhoefer ([15] – [18]). They also represent system disturbances as an antigen.

The pathogen is recognized by the antibody thanks to the epitopes, which are located on the pathogen's surface. Thus epitopes present the pathogen to the immune system. In the case of the combustion process, the influence of the disturbance is expressed through actual process state ({CV, DV, MV} vector) changes. Thus in the SILO system, pathogen represent disturbance and pathogen is presented to the immune system in the form of the process state.

### *B. Antibody*

Antibodies are created by B cells. The task of antibody is to bind the antigen. Each antibody is able to recognize only one sort of epitope. The antibody consist of an antigen binding part and an effector part [19].

In the SILO system the antibody effector part is a vector of MV points' increments, which minimize indicator (1). Thus setting new control vector to the object should compensate the influence of the disturbance on combustion process. This approach is similar to that proposed by Fukuda ([15], [20]). He also treats best solution vector as an antibody.

There are many propositions for defining antibody binding strength (lymphocyte affinity). The measure to calculate lymphocytes' affinity is determined by lymphocyte's representation ([14]). In most optimization problems affinity is evaluated with the use of optimized quality indicator [21]. In SILO a different solution is proposed. We assume that antibody binds antigen only when actual process points' values are similar to process points' values stored in B cell, which creates an antibody. A set of process points can be limited to those points which represent disturbances. In the case when process characteristics are strongly non-linear it is also possible to compare actual (antigen) and previous (antibody) values of MV and CV points. One should notice, that if previous and actual MV, DV and CV vectors are similar, then elements of previous and actual XV (non-measured disturbances) vector are also similar. This correlation has a simple explanation. If XV vectors are distinctly different, then process response {CV} for the same input signals {MV, DV} will be different. Thus lymphocytes will represent different pathogens. Therefore information of rarely or non-measured disturbances is indirectly taken into consideration while evaluating affinity level.

### *C. Lymphocyte - B cell and Th cell*

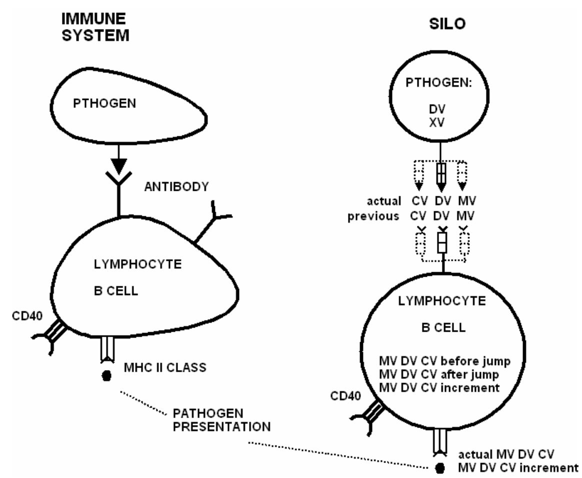
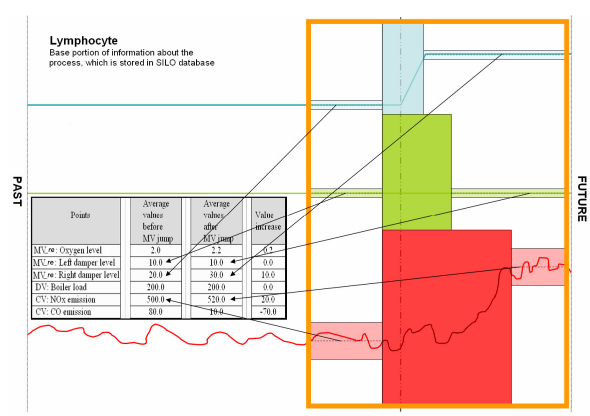



Fig. 5. B cell representation

B cells produces certain types of antibodies. B cells also take part in the immune memory creation process. When an antibody, which is located on the surface of the B cell, binds the antigen, then the pathogen is presented on the surface of the lymphocyte in the context of MHC class II particle. When Th cell recognizes the presented antigen, then it activates B cell to intensive proliferation and differentiation (clonal selection mechanism).

In the SILO system the B cell represents process state before and after a control change. Each pair *process state* and *object's outputs response to control variables' change* represents one B cell. One should notice that the B cell represents the situation only when the process disturbances are constant.




| Points | Average values before MV jump | Average values after MV jump | Value increase |
|---|---|---|---|
| MV_re: Oxygen level | 2.0 | 2.2 | 0.2 |
| MV_re: Left damper level | 10.0 | 10.0 | 0.0 |
| MV_re: Right damper level | 20.0 | 30.0 | 10.0 |
| DV: Boiler load | 200.0 | 200.0 | 0.0 |
| CV: NOx emission | 500.0 | 520.0 | 20.0 |
| CV: CO emission | 80.0 | 10.0 | -70.0 |

Fig. 6 B cell example

TABLE I
B CELL EXAMPLE

| Points | Average values before MV jump | Average values after MV jump | Value increase |
|---|---|---|---|
| MV: Oxygen level | 2.0 | 2.2 | 0.2 |
| MV: Left damper level | 10.0 | 10.0 | 0.0 |
| MV: Right damper level | 20.0 | 30.0 | 10.0 |
| DV: Boiler load | 200.0 | 200.0 | 0.0 |
| CV: NOx emission | 500.0 | 520.0 | 20.0 |
| CV: CO emission | 80.0 | 10.0 | -70.0 |

Antigen presentation on the surface of the B cell, consists of *actual process state* and *MV points (input) influence on CV points values (output)*. Th cell takes a decision about B cell activation, based on indicator (1).

## V. Optimization Algorithm

The immune optimizer minimizes quality indicator presented below ([22] – [23]):

$$J = \sum_{k=1}^{N} \left[ a_k \cdot \left| K_l (ap_k - sp_k) \right| + b_k \cdot \left( K_k (ap_k - sp_k) \right)^2 \right] \qquad (1)$$

where:

$$K_l(ap_k - sp_k) = \begin{cases} |ap_k - sp_k| - zone_l \text{ if } |ap_k - sp_k| > zone_l \\ 0 \text{ if } |ap_k - sp_k| \le zone_l \end{cases}$$

$$K_k(ap_k - sp_k) = \begin{cases} |ap_k - sp_k| - zone_l \text{ if } |ap_k - sp_k| > zone_k \\ 0 \text{ if } |ap_k - sp_k| \le zone_k \end{cases}$$

- $N$ total number of points from MV and CV group.
- $ap_k$ current value of k-th point
- $sp_k$ set point value for k-th point
- $a_k$ weight for the Linear Penalty Coefficient for k-th point from MV or CV group
- $b_k$ weight for the Square Penalty Coefficient for k-th point from MV or CV group
- $K_l$ linear insensitivity zone operator
- $K_k$ square insensitivity zone operator

The layers of the optimization algorithm are shown in Fig. 7. Function of each layer is described below.

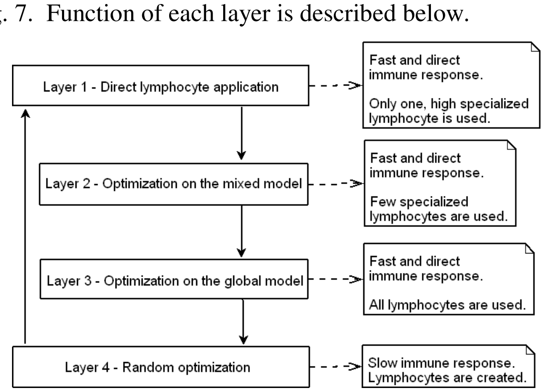



Fig. 7. Optimizer layers

### A. Layer 1 - direct application of lymphocyte

In this layer only one B cell is activated from the group of all lymphocytes, which fulfill the affinity condition (which binds the actual antigen – refer chapter IV-B). This B cell has antibodies (MV increments) which cause the biggest drop of the indicator (1). In other words, in this layer only one control vector increment (antibody) is chosen (from the set of the B cells stored in data base, which represent a similar process state), being the one which results in the most desired change in process outputs in the context of the quality indicator (1).

If the solution found in this layer turns out unsuccessful, the program is switched to layer 2 or 3.

### B. Layer 2 – Optimization on the mixed model

In the second layer all B cells, which fulfill affinity conditions (refer chapter IV-B) are activated. An incremental linear mathematical model is automatically constructed based on those B cells. This is the so-called local model. This model represent MV vector increment's influence on CV vector increment:

$$\Delta CV = K \cdot \Delta MV,$$

where $K$ is the gain matrix. Local model is constructed only on the basis of B cells which represent similar process states. Thus the local model is constructed in the locality of the actual working point, so the linear model is sufficient.

In this layer the global model is also constructed. The form of the global model is the same as the local model. The global model is automatically constructed on the basis of all B cells stored in immune memory. Local and global models are mixed with different weights. The global model is used only to improve the robustness of SILO. In the case of strongly nonlinear processes the global model can be disabled in layer 2.

The quality indicator (1) is minimized based on the linear, mixed model. The optimal control vector is set to the boiler. It causes the creation of a new B cell, which is then saved in the immune memory.

When the mixed model is constructed, before performing optimization on the model, some of the elements of the MV vector are blocked with certain probability. Blocked control variables are fixed, and the dimension of the optimization task is reduced. It causes mutation in the new B cell (new control vector, which is the result of the optimization).

### C. Layer 3 – Optimization on the global model

The third layer is similar to the second layer. In the third layer only the global model is constructed, but the optimization method is the same. The third layer is activated when the immune memory is too small to build a local model (initial stage of SILO operation or system is attacked by unregistered disturbance).

If the solution found in this layers turns out unsuccessful, the program is switched to layer 4.

### D. *Layer 4 - random optimization*

During the initial stage of program operation the immune memory is relatively small and it frequently happens that the system is attacked by unregistered pathogens. In this layer random movements of MV vector elements are performed. Those movements (micro-tests) are performed in the locality of the actual working point.

Apart from generating new lymphocytes, thanks to applying special heuristic, this layer also causes a reduction in the quality indicator (1). If a movement of a selected MV vector element caused an improvement of the quality indicator (1) then the direction of this movement is remembered and the next movement is performed in the same direction (e.g..: increase damper opening). If the quality indicator (1) is worse after performing a movement, then the direction of the movement is reversed. Only one movement on one MV point is performed at a time. This point is randomly selected from the group of all MV points every time.

After defined number of movements the program is choosing the best MV points configuration obtained in Layer 4. Then the program is switched to Layer 1.

### E. *Innate immune system*

Thanks to the innate immune system the body is born with the ability to recognize certain pathogens and immediately destroy them [12]. After SILO installation, and before launching the program, the user can define some defense scenarios, against the attacks of some well known pathogens. Below we presented one examples of such defense scenario:

- If the coal mill is turned off (an element of the DV vector), then the boiler dampers related to this mill must be closed (an elements of the MV vector);

## VI. Learning Module

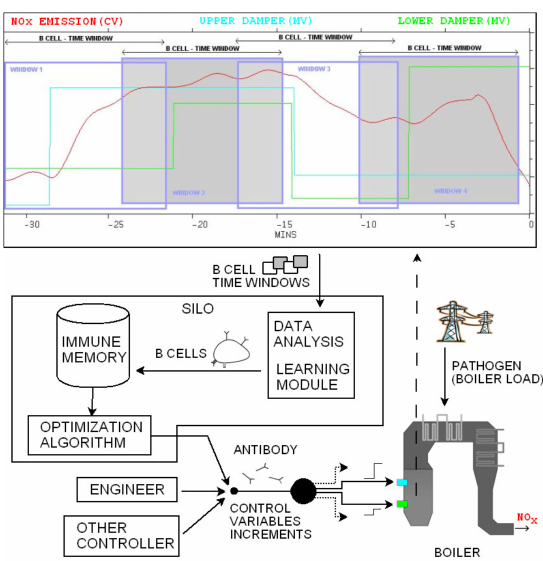



Fig. 8. General idea of SILO

The *learning module* is responsible for storing a B cells in the immune memory. This module analysis actual and historical process's points values in search of *time windows* which fulfill the criteria of being a B cell (constant disturbance, control vector change). This module is fully independent from the *optimization module*. The *learning module* is able to find and store B cells:

- which were created by SILO's *optimization module,*
- which were created as the result of the intervention of the boiler operator,
- on the basis of the file, which contain process's historical data (batch learning).

During boiler operation new B cells are created all the time. The *learning module* saves them in immune memory, and they are used in first, second and third layer of the optimization algorithm (refer Fig. 8). Thus the knowledge about the combustion process is continuously updated and used in the optimization algorithm. Thanks to this ability SILO is able to quickly adapt to boiler changes.

## VII. Results from Newton Power Station

SILO was implemented on each of three units in Ostroleka Power Plant (Poland, max. unit load 240 MW) and on first unit in Newton Power Plant (USA, max. unit load 615 MW). Results from Ostroleka Power Plant was presented in [23].

In this article the second implementation of SILO in Newton Power Plant is presented. Results from first SILO implementation in Newton Power Plant and the comparison between results obtained by SILO and MPC controller are presented in [24].

SILO goals in Newton Power Plant was to minimize NOx emission and keep average CO emission below 400 PPM.

TABLE IV
MV, DV and CV vectors

| | Aggregates | SILO | | |
|---|---|---|---|---|
| | Controlled devices | MV vector | CV vector | DV vector |
| Size | 17 | 8 | 2 | 9 |
| Elemnets | O2 level | O2 level | NOx emission | Boiler load |
| | Four SOFA tilts | Windbox | CO emission | Mills configuration |
| | Fuel Air dampers | Three feeders (D, E, F) | | Water temperature in the Newton Lake |
| | Windbox pressure | Three SOFA tilts | | Burner tilts |
| | Upper COFA damper | | | |
| | Three SOFA dampers | | | |
| | Six feeders | | | |

SILO configuration parameters were tuned in three days after SILO installation in Newton Power Plant. Initial learning process took another four days. One week after installation, three *on/off* tests was performed. The results of these tests are presented (one test per day).

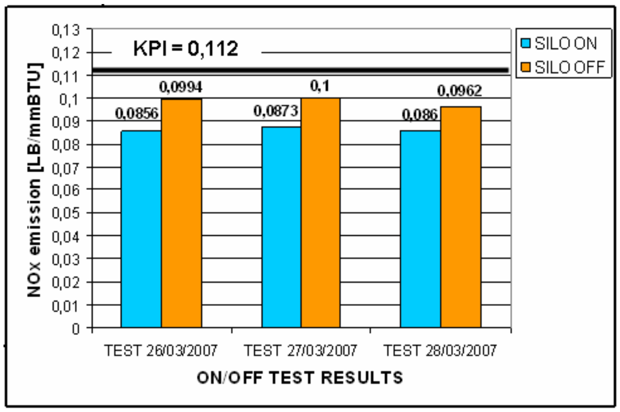



Fig. 9. NOx emission results in Newton Power Plant

At the maximum load SILO decreases average NOx emission by 12,4 %, and never exceeds the CO emission limit set by the Power Plant management.

Analysis of SILO operation in Ostroleka Power Station and in Newton Power Plant, allows us to formulate the following conclusions:

- SILO is able to continuously control the combustion process. SILO was turned off only in the case of failure of the coal mills.
- SILO is able to effectively react to disturbance changes without operator intervention.
- SILO distinctly reduces NOx and CO emission without deterioration of boiler efficiency and super-heat steam temperature.

## VIII. Conclusions

In this article we present SILO – immune inspired solution for combustion process optimization. Main goal of this solution is optimization of power station's variable costs, achieved by combustion process optimization, especially by CO and NOx emission minimization. In comparison to standard MPC controllers, the main advantages of this solution are presented below:

- it decreases implementation costs by reducing the time involvement of highly qualified engineers (there is no need to build complex models after SILO installation – static models are automatically constructed);
- on-line learning and adaptation to new environment.

The main SILO disadvantage (in comparison to MPC controllers) is that it doesn't use dynamic model of the process. This is why this solution is not sufficient for mostly regulating units. The SILO system is a good and cheap alternative to MPC controllers in case of units, which keep steady load in a long periods of time (for example: *base load* units).

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