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BLAST FURNACE KNOWLEDGE-BASED CONTROL BY MEANS OF SIMULATION

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Abstract: In this paper is presented an approach of blast furnace knowledge-based control supported by mathematical models. The developed mathematical models are used for state observation, static simulation, and dynamic simulation. Fuzzy knowledge approach was used for the decision. Both the models and knowledge base are simultaneously used in the control system synthesis. The control alternatives are determined by means of knowledge base and can be tested by the model. *Copyright © 2002 IFAC*

Keywords: control system, on-line control, process models, process control, model-based control.

1. INTRODUCTION

Blast furnace (BF) process control is one of the main contributor to the successful blast furnace operation and belongs to the key factors of its economic effectiveness. Blast furnace process complexity in combination with growing demand on effectiveness and reducing environmental impact has necessitated a change in process control strategy. In the past, static calculations based on black-box principles were used to predetermine some fundamental set points with limited feedback from the process. This type of control can give acceptable results only when the process has small deviation from a stationary operating point. Because of process instability small disturbances can cause significant deviation from the operating point which requires set point correction for which AI methods are generally used (Brunnbauer, *et al.,* 1999 ; Matsuda, *et al*., 1994).
With variation in the charge composition and various operating practices the dynamics of the process has to be taken into account providing recalculation of set points and immediate feedback in real time. One precondition for the dynamic process control was the development of the sensors and measuring techniques which give real time information about the process state. The evaluation of dynamic models makes it possible to go from process supervision to proactive real time control. Different approaches reflect specific situation and control philosophy (Kowalski, *et al.,* 1995; Inkala, *et al.*, 1995; Nemčovský, 1999). The main aim of this paper is to point out alternative approach based on simulation and knowledge-based control synthesis.
The problem of blast furnace automatic control is very hot and new approaches leading to the improvement of its performance are continually wanted. Consequently, a control synthesis procedure should be found in order to deal with the BF control problems.

2. BLAST FURNACE MODELLING

The BF is a complex technical system and a single model can´t cover all the control needs. Therefore for control purposes three categories of models were developed:

- models for state observation
- static simulation model
- dynamic simulation model

Each model category has the ability of modelling multiple system aspects at different levels of abstraction for specific control steps.

Models for state observation; The purpose of state observation models is to continuously display the process status. They allow to control various process parameters with the applicable process strategy. Determination of the process status is based on the information retrieved from field instrumentation. Developed models are specified in Table 1. Models are of analytical, empirical and heuristic nature. The calculation runs cyclically and the output from these models are: geometrical, thermal and material state of the furnace and its parts.

Static simulation model; For required pig iron grade the associated charge and heat and mass balance calculation is performed. The calculation is based on stoichiometric balance with consideration to field factors such as wind temperature and predicted heat losses of furnace walls and gas, alkali content etc. The calculation aims at reaching requested melting intensity, pig iron composition and temperature and slag basicity. Further, wind parameters are calculated, also optimal flame temperature, optimal heat and gas utilization as far as economic indexes. From heat and mass balance equations for required pig iron volume, charge composition, powder coal combustion, required fuel for Si, Mn, P, S reduction optimal wind volume is calculated in respect to furnace optimal specific wind volume with limitation on combustion condition of powder coal (O_2 content in the wind). The calculation algorithm is in Fig. 1. The output from the model is metallic charge composition, slag builders to be added with respect to slag basicity, coke amount, wind parameters and injected fuel. Based on the results from the heat and mass balance calculation standard set points are determined so as to comply with actual requirements. The enlarged heat and mass balance calculation gives upgrade information about slag composition, technological and economical process characteristics. The calculated values serve as a standard.
The operator can switch the model any time at least six times a day when current data about sinter are available or the requirements of the steel plant are changed. It is possible to generate some alternatives as decision support.

Dynamic simulation model; The purpose of dynamic model is to give forward information about the BF process development and decision support for evaluation of selected alternatives. Predictive model represented virtual furnace which is fed with real-time input information. The model output information are ahead of the real-time.
The model is of zonal type (Dorčák, *et. al*, 2001). Vertically, each zone consists of one or more charges, horizontally, the furnace is divided into 8 rings, 8 segments and 64 elements. Each zone represents sub-processes which take place in the corresponding part of the furnace. The dynamic development is expressed by balance equations of the individual substances in the particular zone in the discrete form

$$x_{k+1} = x_k + Bu_k \qquad (1)$$

where k is the discrete step of dynamical development, x_k is the n-dimensional state vector at step k. Its components express the states of elementary sub-processes, like mass, temperature, chemical composition and u_k is m-dimensional input vector at step k. Its components represent running sub-processes such as transport and generation. B is mxn dimensional structural matrix expressing proportionality relations.
The predictive model makes real-time simulation based on current data about the furnace inputs. The modeled processes are: gas flow, material flow, thermal processes, chemical processes, physical processes and geometrical processes. The furnace state is determined for each element.

3. CONTROL SYSTEM SYNTHESIS

There are many methods of control synthesis suitable for continuous and discrete time system. However, they are not suitable for solving control synthesis of such large scale and complex system as blast furnace is. Its behaviour is influenced by occurrence of different situations in its subsystems.
The classical control theory does not give satisfactory general results in analysis and control synthesis because of neglecting its complexity. Consequently, different methods of control synthesis are required. Our approach is based on the furnace model as well as rule-based representation of knowledge of the control task.
The model is able to describe the system to be controlled, but it does not yield any directions about how to control the system. Consequently, control synthesis procedure should be found in order to deal with the blast furnace control problems.
The control synthesis problem is that of finding a sequence of control vectors u_k, k=0,1,…n that are able to transform the controlled system from the given initial state x_0 to the prescribed terminal state x_k.
However, as a rule, the blast furnace control policy can't be expressed in analytical terms. Knowledge concerning the control tasks specifications (e.g. constrains, criteria, etc.) is usually expressed only verbally . Consequently, the proper knowledge-based representation (the rule base one) is needed in form

Table 1 Blast furnace observation models

Type of model	Basic input variables	Output variables	Modelling principles
Gas distribution in the shaft	- top gas temperature	- centricity - peripherity - asymmetry	Analogy temperature-velocity
Raceway parameters	- wind temperature - wind velocity - melt level in hearth	- raceway shape and geometry - dynamic resistance index	Empirical laws
Shaft temperature distribution	- top gas temperature - material flow	- position of isotherms 500 °C, 700 °C, 900 °C, 1200 °C, 1300 °C.	Countercurrent heat transfer
Furnace thermal state	- heat losses by gas - heat losses by wall	- deficit or excess of heat	Heat balance
Dropping zone characteristic	- melting intensity - gas volume and temperature	- pig iron and slag temperature and chemical composition	Local zone model
Hearth liquid level	- melting intensity - dimension of hearth - tapping intensity	- pig iron and slag level	Viscous flow dynamics (heart, tapping hole)
Geometry of material zones	- shaft temperature distribution	- shape and position LTTR, cohesive zone, dropping zone, dead man	Material isotherms geometrical distribution
Shaft geometry (scaffolds)	- wall heat losses	- thickness of scaffolds	Heat transfer equation

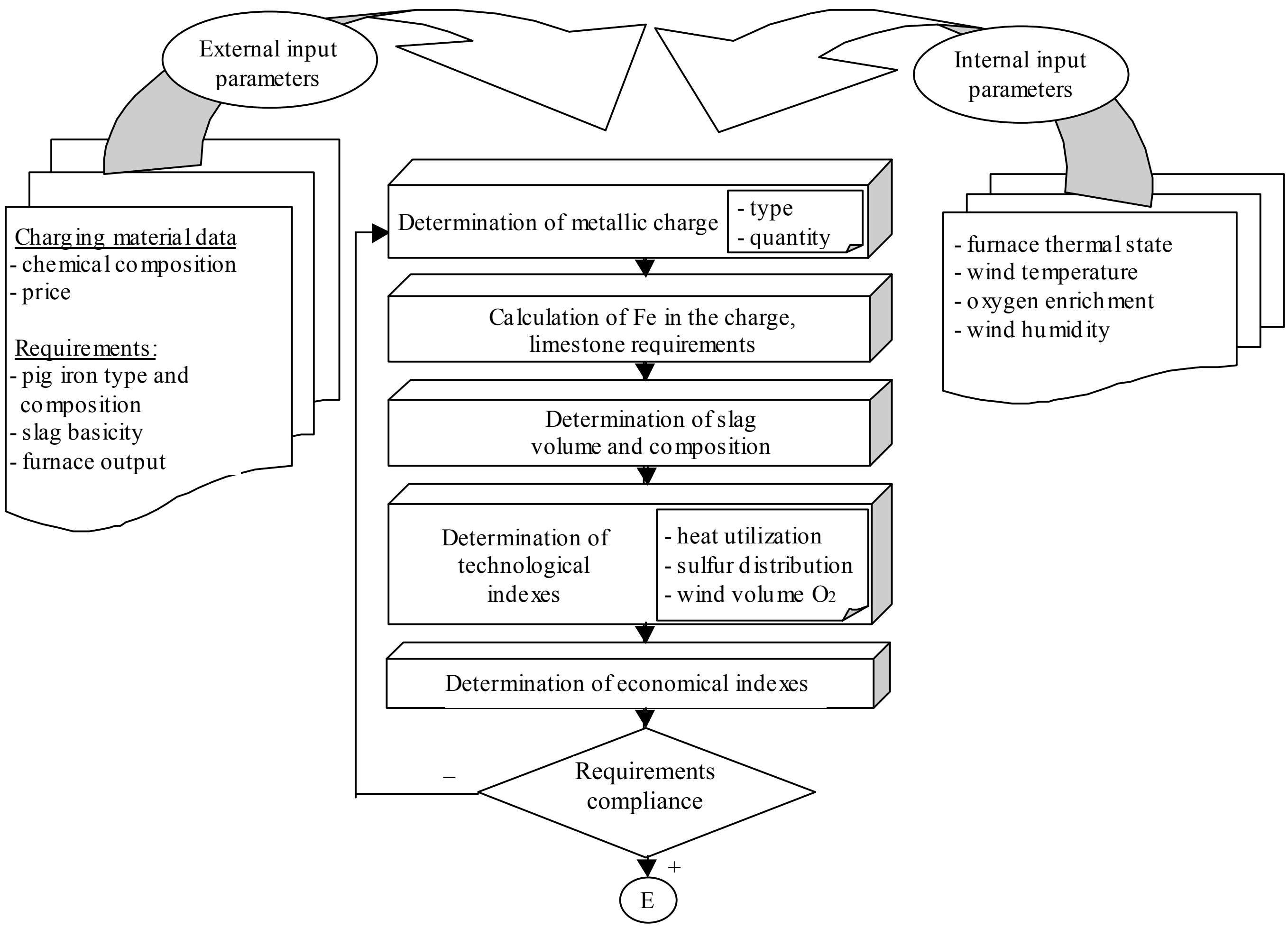

Fig. 1. Blast furnace static simulation model

of a domain-oriented knowledge bases. The knowledge base is utilised at the choice of the most suitable control vector u_k at any step k when there are several possibilities (in order to avoid any ambiguity) as to the further development of the BF dynamics. In order to find the suitable control vector u_k able to transform the system from the existing state x into a following state x_{k+1} the following procedure has been used

START

k=0
$x_k = x_0$, x_0 is an initial state, x_d is an desired state

LABEL

- generation of the control base w_k
- generation of the possible control vectors $\{u_k\} \in w_k^k$
-generation of the corresponding model responses $\{x_{k+1}\}$
-consideration of the possibilities in knowledge base (IF THEN rules) and expressing control tasks specifications.
- choice of the more suitable control possibilities

END

This procedure is schematically illustrated in Fig.2. where w_k are transitions that can theoretically be enabled at step k. It represents the control base because it expresses the possible candidates for generation of a control vector $\{u_k\}$ at step k. Its components point out the possible events which could be utilised in order to transfer the system from the present state x_k into the state x_{k+1}.
When only one of the w_k components is different from zero it can be used to be the control vector i.e. $u_k = w_k$. When several components of w_k are different from zero, the control vector u_k has to be chosen based on additional information about the actual control task.
The choice of the control vector can be made either by a human operator or automatically on the basis of a corresponding domain oriented knowledge representation in the form of IF – THEN rules predefined by an expert in the corresponding field.
Such a knowledge base consists of a suitable expression of the constraints imposed upon the task in question, criteria and further particulars concerning the control task or the controlled object.
For obtaining the elementary control vectors $\{u_k\} \in w_k$ a suitable generation procedure was used

$$u_k = \{u_1^k, \ldots, u_m^k\}^T \tag{2}$$
$$u_k \subseteq w_k \tag{3}$$

$$u_j^k = \begin{cases} w_j^k \text{ if chosen} \\ 0 \text{ otherwise} \end{cases} ; j = 1,..,m \tag{4}$$

Control vectors can contain single or more non zero elements of the base vector w_k.

3.1 The knowledge representation

The suitable form of the knowledge representation is needed in the control synthesis procedure to decide which control possibility should be actually chosen at any step k. The fuzzy rule-based knowledge representation was used to construct the knowledge base (KB).
The control system is working with many input and output variables. The number of rules is growing with the number of linguistic variables and such a great number of rules significantly complicates KB design. For this reason the KB has hierarchical structure as in Fig. 3 where x_i are input statements, w_i are intermediate statements, u_j are output statements, R are the rules in the form of IF- THEN structure. The rules can be evaluated with fuzzy measure within the boundary values <0,1>. The rules R_n refer to the furnace parts according to its decomposition into eight zones. The rules R_g are generating the global decisions.
This approach significantly reduces the number of rules and simplifies the verification procedure. The control system includes 46 input variables x_i (18 are original process data and 28 are derived features) with three linguistic values and 9 output variables u_j. The number of rules is 138 of Mamdani type. Process dynamics is built up through input variables. The time horizon is determined by the dynamics of the particular processes and changes from 5 minutes to about 8 hours. The decision process is shown in Fig.4.

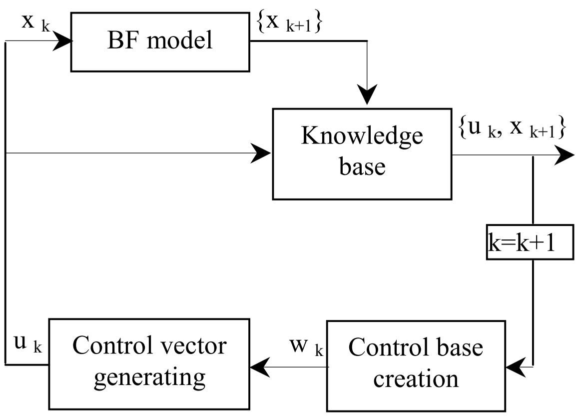

Fig. 2. Control system structure

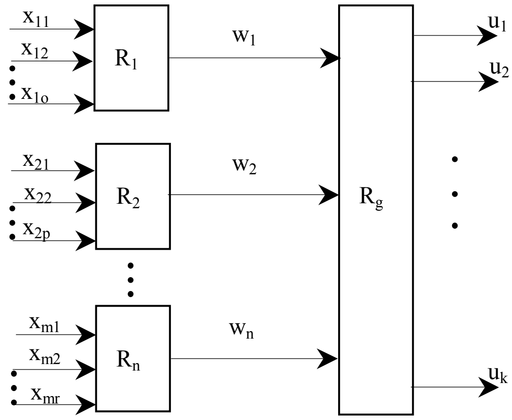

Fig. 3. Hierarchical knowledge base

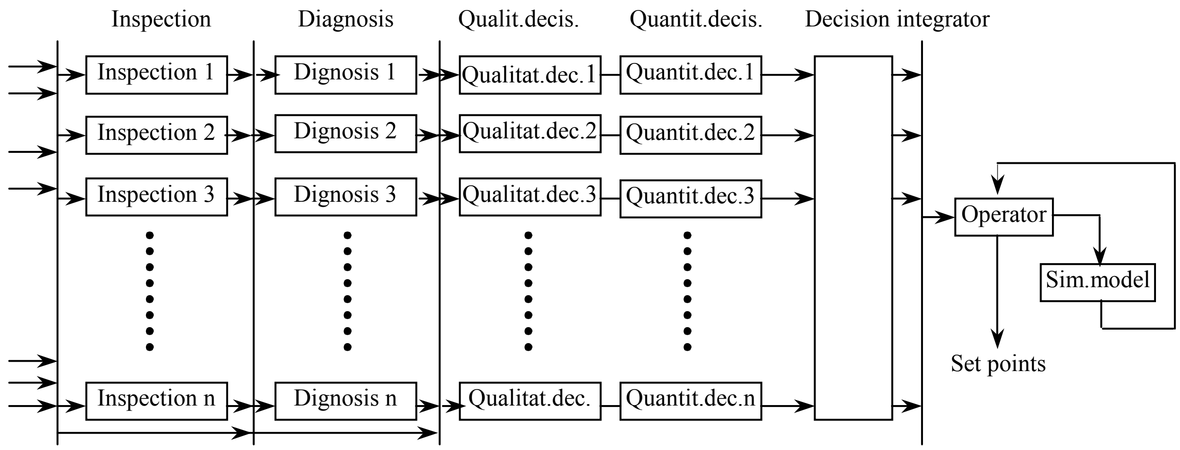

Fig. 4. Decision process representation

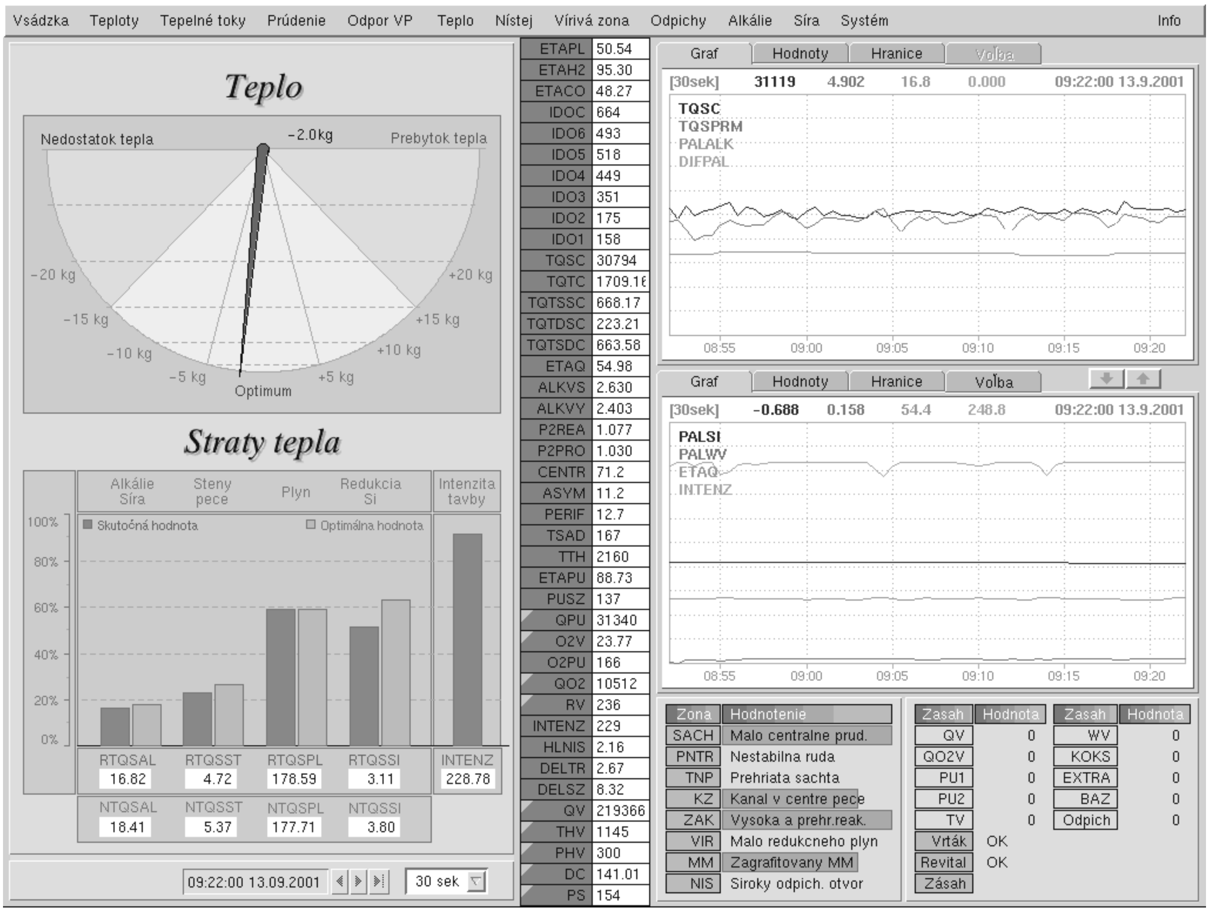

Fig. 5. Operator display

4. APPLICATION

The main purpose of the process control system is to reach specified pig iron composition at the tap, temperature at the tap and volume. The outputs from the process control system are set points of: charging material composition, coke ratio, charging material distribution, blast wind volume, blast wind temperature, blast wind moisture, oxygen injection, fuel injection, tapping time and tapping intensity. The set points are determined to fulfill process requirements (productivity and quality) with minimal energy and material costs.

The structure of the presented control system is hierarchical and has three decision levels: strategic, tactical and operative. On the strategic level charging material composition is determined. Decision is based on static model simulations. On the tactical level energy inputs and charge distribution to reach desired (optimal) process trajectory characterized by heat balance and temperature distribution are determined. For the decision predictive model is used.

Operative decisions are for the correction of process disturbances detected by dynamic models. Because gas flow distribution has major influence

on the process behaviour, it is the correction of the gas distribution and liquid level which can be effectively used for its influence. On top of the control system is acting supervisor. Its main goal is to increase the operating availability of the process under control and to optimize the process performance according to metallurgical and economical benefits.
To achieve this, the operator should coordinate the actions of the distributed controllers, according to the evolution of the process variables or functional relationship among them.
Because of strong interaction between control loops optimum combination of set points changes and an optimum time schedule can be chosen.
The advantages of the above-described control system are in its white box dynamic nature and dominated feed-forward control. The disturbances are eliminated at the local level so that global disturbances are avoided. Process status is immediately detected and process set points dynamically updated. Energy efficiency is determined in real time and is reflected instantly in the operating conditions.

Table 2 Improvement of the BF results with process control.

		Before process control	With process control
Production	thm/day	3358,0	4123,6
Fuel consumption	kg/t hm	495,3	484,6
Coke consumption	kg/t hm	396,6	367,64
Powder coal	kg/t hm	109,7	137,04
Melting intensity	t/m^3 .d	1,786	2,193
Time efficiency	%	89,19	91,07
PI Enrichment	%	58,36	57,99
Slag rate	kg/t hm	355,9	353,71
O_2 enrichment	%	23,96	23,91
Wind temperature	°C	1096	1131
Charge	kg/t hm		
Sinter		1166	1154
Acid pellets		348	409
Basic pellets		132	116
Recycl.waste		-	14
Limonite		46,9	28
Charge quantity			
Coke	t	7,8	6,8
Ore	t	34,1	34,5
Pig iron:	Si	0,64	0,59
	Mn	0,57	0,46
	S	0,034	0,033
T_{hm}	°C	1452	1468

When the operator is faced with the same kind of problem each prefers his own strategy. So different actions are taken in different operating shifts. Inconsistent operating rules and lack of control loop coordination are therefore usually present. The hardware used are PC-based systems with QNX operating system. Data are shared by SQL database. Process signals are exchanged via profibus. Communication with the operator is via twelve screens. One of them is shown in Fig. 5. The control system is in detail described in (Nemčovský, 1999).
The developed control system was applied at blast furnace No.3 Steel Košice and brought overall improvement (Table 2).

5. CONCLUSION

The developed blast furnace control system relies on its decomposition into functional zones. The state observation and diagnosis on local level enables to influence disturbances before their appearance on global level. The blast furnace heat control, based on local heat balances, enables intervention in much shorter time intervals than is the blast furnace inertia. The control system is open and individual modules can be continuously improved. Mathematical models as integral part of the control system allow its forward control. Decisions recommended by the control systems respect priorities of dominant processes in each zone. Application of the presented control system enabled to increase furnace productivity by 30%, increase powder coal consumption by 30 % and decrease furnace heat reserve by 2,5%.

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