USAGE OF ANALYTICAL DIAGNOSTIC FOR OPERATIONAL CONTROL SUPPORT ON STEELWORKS

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Abstract

The regression model for operational control support on steelworks based on analytical diagnostic is described in this work. The regression model is the base for knowledge planning system. The usage of model lies on determination of smelting count, which are able to cast with minimum risk of nonstandard product occurrence. The result is combination of number of steel smelts. The user can choose a proper combination based on production order.

Keywords: Steelworks, operation control, diagnostics, knowledge systems, model

1. INTRODUCTION

The production process is governed to many random influences, which appear as failures from the point of goal achievement. The causes of these influences could be:

- materials and semi product quality variation,
- unpredictable load changes,
- lack of energy,
- instruments and machines failures,
- technological discipline fault,
- wrong and slow evaluation of complex situations and so on.

Technological process control is one of the most wide control area of production process. Production process control involves following tasks, according to production character:

- production scheduling,
- operative production control,
- technological processes and devices control.

This work is focused on interconnection of operative control with production scheduling. The objective is to make the optimal production schedule, respectively to achieve conformity between production demands and production possibilities. In other words, the goal of the production scheduling is composition of optimal production tasks schedule. The main tasks are solved here:

- transformation of orders to shift level,
- order throughout verification, which is assignment of single operations to specific interval on time scale of specific machine and so on.

A necessary condition is to meet criteria of production quality and respect all restrictions (capacitive, technological and so on).

Generally production scheduling can be defined as follows: It is given a set of specific production sources with known distribution of theirs possibilities during given scheduling plan. Further the file of production tasks is given with known demand distribution arising from its fulfilment. For every single production task, it is necessary to plan its end in specific time interval. The goal is to terms for fulfillment ending of each production task in term of time interval. It has to be comply as good conformity of capacitive demand with time possibilities as possible.

The criterion function could be for example standard deviation or mean absolute deviation between capacitive possibilities and demands. In given cases could be a criterion for optimal control thinner, such as minimization of costs or maximum production device usage. [1]

On that level of control, the computer is only a tool with automation calculations. It makes easier to try various solution variants. The computer does not interfere into the production process, it only works as a computer - advisor, in other words - it is offline type.

When the standard tasks are solved in more complex production systems (for example steelworks with continuous casting device) total variants of numbers are so high, that the computer is not able to try every single possibility (the task cannot be solved exactly). It is needed on the experiences basis, analogical solutions, but also an intuition and so on to use heuristic (non-algorithmic able) methods to limit number of variants. Here is a necessary condition: the total number of criterion functions runs in reasonable time. The only human role in the process lies in the control of production scheduling. [2]

Further presented regression model of mold weariness, which characteristics are the work’s goal and which is based on analytical diagnostics and clustering analysis, represents a new approach to support production scheduling. This is done by combination of standard and non-conventional (mentioned above) approach to this problematic.

2. OPERATIVE CONTROL ON CONTINUOUS STEEL CASTING DEVICES

One of the basic assumptions when increasing continuous steel casting device’s (CSCD) productivity is increasing number of smelts casted in one sequence. During steel grade the change is happened in melting ladle and also in liquid core of congeable blank to mutual mixture of these grades. This results to such grade, which is not the same as previous grade, nor current grade. In continuous casted blank originating composite or transition area, whereas the goal of all manufacturers which using CSCD is to minimize this area respectively foresee its real range.

Technological point of view: if the given smelts has different chemical composition of casted steel, it will originate in ladle to mix old steel grade with the new one. This situation comes out in distinct chemical composition of casted steel, which does not respond to current or previous quality - originating composite area. The influence of this area on each casting currents is given by [2]:

- mainly distinctness of chemical composition of mixture areas,
- also by weight of steel in the ladle, by temperature difference of both steel grades,
- regime of the ladle filling in the time of mixing the grades,
- as a count of functional casted currents, by position of steel nozzle output from the tundish to the main ladle and also by the shape of main ladle.

Above mentioned transient effects could have significant influence not only to steel flux character in tundish and also to mixing intensity, but also to temperature instability of casted steel in every current. This can lead to increasing possibility of defect occurrence in blanks or, in extreme, to breach out.

As mentioned above, the conclusion is that production scheduling on CSCDs introducing complex problems, which include many external influences, which are given as by technological parameters, so by commercial parameters character. The goal of production scheduling is to complete a casting schedule where takes place steel grades in demand quality and quantity, which is in conformity with customers and production possibilities in given time period. [3]

2.1. The operative control model with usage of analytical diagnostic

In further text will be presented a proposal of production scheduling algorithm for continuous steel casting device in mold end time period. In qualitative point of view it means to maintain [4]:

- a stability of operation when casting
- a requisite casting speed with drawing bench speed, which task is to traction of the blank
- a quality of blank in context with its:
  - inner structure,
  - surface structure,
  - dimensional accuracy.

For this type of task planning expert systems are used (also generative expert systems). When the tasks are solved in planning expert system, there is known the final goal and initial state. The task of the system is with data usage about given case to found an optimal sequence of steps (operators), which are critical to achieve given goal. The result is a list of suggested solutions, which are evaluated by certain optimality. The important part is a generator of possible solutions, which automatically generate, combines and tests allowable solutions. Chosen solutions are tested on data from data basis. In context with combining solutions when creating steps sequence, we are talking about “combinatory explosion”. This explosion limits only knowledge of expert and data about given case. In **Figure 1**, it is presented typical architecture of planning expert system. Control mechanism affects the choice of allowable operators, control conformity of generated solutions with basis data and in that way makes reservoir of potential solutions. [5]

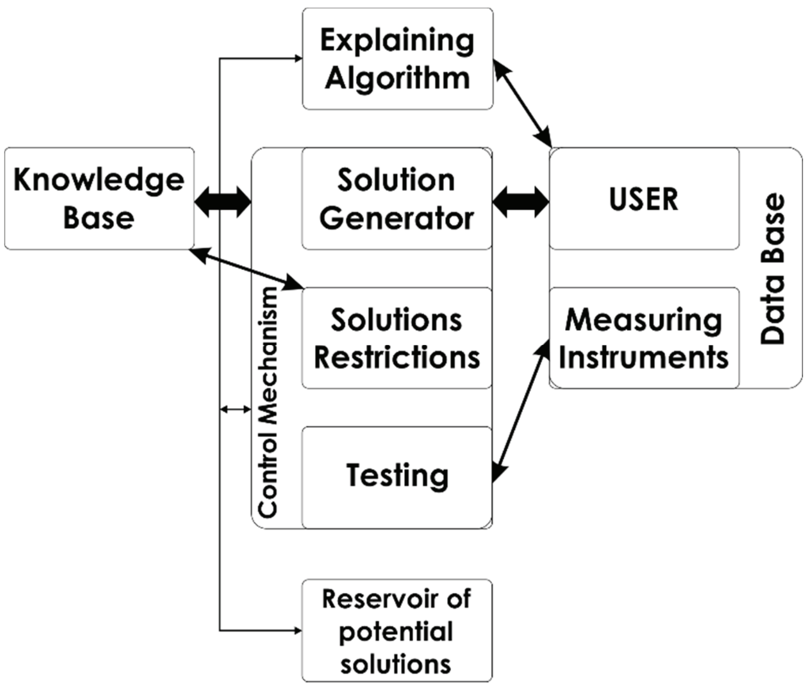

Figure 1 Architecture of planning expert system

In **Figure 1** is presented block scheme an architecture of planning expert system, utilizing a principle of generating and testing of allowable solutions. Control mechanism will also [6]:

- influence choosing of allowable operators;
- limits generative ability of generator by using knowledge base information (for example refusing some sequence steps and so on);

- conformity testing control of generated solutions with data from data base, and that's why making reservoir of potential solutions, including its fitness.

Effectiveness of whole expert system is influenced by knowledge base quality. [7, 8] The knowledge base in this case represents deterministic model which is based on analytical diagnostics of mold state. The model can be visualized by scheme in **Figure 2**.

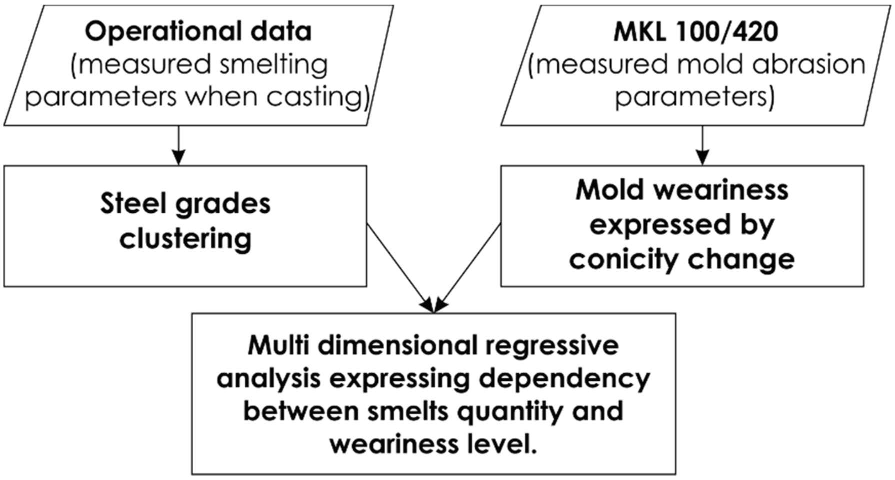

Figure 2 Model structure presentation

The model has a character of multi-dimensional regressive function, expressing dependencies of mold weariness to number of smelts in given steel grades clusters.

In this phase of analysis is testing multi-dimensional linear regressive model in shape of:

$$\beta_0 + \beta_1 \cdot f_1 + \beta_2 \cdot f_2 + \beta_3 \cdot f_3 + \beta_4 \cdot f_4 + \beta_5 \cdot f_5 = \Delta k_d \quad (1)$$

Where f_1 to f_5 are cumulative occurrences of casted grades in clusters S_1 to S_5, β_1 to β_5 are weariness coefficients of importance for clusters S_1 to S_5, β_0 is shift coefficient, Δk_d is average conicity change in circle mold type in various time period. [9]

The model is solved with help of least squares technics which means:

$$S(\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5) = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (\Delta k_{di} - \beta_0 - \beta_1 \cdot f_{1i} - \beta_2 \cdot f_{2i} - \beta_3 \cdot f_{3i} - \beta_4 \cdot f_{4i} - \beta_5 \cdot f_{5i})^2 \quad (2)$$

The result is equation system in shape:

$$n \cdot \beta_0 + \beta_1 \cdot \sum_{i=1}^{n} f_{1i} + \beta_2 \cdot \sum_{i=1}^{n} f_{2i} + \beta_3 \cdot \sum_{i=1}^{n} f_{3i} + \beta_4 \cdot \sum_{i=1}^{n} f_{4i} + \beta_5 \cdot \sum_{i=1}^{n} f_{5i} = \sum_{i=1}^{n} \Delta k_{di}$$

$$\beta_0 \cdot \sum_{i=1}^{n} f_{1i} + \beta_1 \cdot \sum_{i=1}^{n} f_{1i}^2 + \beta_2 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{2i} + \beta_3 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{3i} + \beta_4 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{4i} + \beta_5 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{5i} = \sum_{i=1}^{n} \Delta k_{di} \cdot f_{1i}$$

$$\beta_0 \cdot \sum_{i=1}^{n} f_{2i} + \beta_1 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{2i} + \beta_2 \cdot \sum_{i=1}^{n} f_{2i}^2 + \beta_3 \cdot \sum_{i=1}^{n} f_{2i} \cdot f_{3i} + \beta_4 \cdot \sum_{i=1}^{n} f_{2i} \cdot f_{4i} + \beta_5 \cdot \sum_{i=1}^{n} f_{2i} \cdot f_{5i} = \sum_{i=1}^{n} \Delta k_{di} \cdot f_{2i}$$

$$\beta_0 \cdot \sum_{i=1}^{n} f_{3i} + \beta_1 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{3i} + \beta_2 \cdot \sum_{i=1}^{n} f_{2i} \cdot f_{3i} + \beta_3 \cdot \sum_{i=1}^{n} f_{3i}^2 + \beta_4 \cdot \sum_{i=1}^{n} f_{3i} \cdot f_{4i} + \beta_5 \cdot \sum_{i=1}^{n} f_{3i} \cdot f_{5i} = \sum_{i=1}^{n} \Delta k_{di} \cdot f_{3i}$$

$$\beta_0 \cdot \sum_{i=1}^{n} f_{4i} + \beta_1 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{4i} + \beta_2 \cdot \sum_{i=1}^{n} f_{2i} \cdot f_{4i} + \beta_3 \cdot \sum_{i=1}^{n} f_{3i} \cdot f_{4i} + \beta_4 \cdot \sum_{i=1}^{n} f_{4i}^2 + \beta_5 \cdot \sum_{i=1}^{n} f_{4i} \cdot f_{5i} = \sum_{i=1}^{n} \Delta k_{d\,i} \cdot f_{4i}$$

$$\beta_0 \cdot \sum_{i=1}^{n} f_{5i} + \beta_1 \cdot \sum_{i=1}^{n} f_{1i} \cdot f_{5i} + \beta_2 \cdot \sum_{i=1}^{n} f_{2i} \cdot f_{5i} + \beta_3 \cdot \sum_{i=1}^{n} f_{3i} \cdot f_{5i} + \beta_4 \cdot \sum_{i=1}^{n} f_{4i} \cdot f_{5i} + \beta_5 \cdot \sum_{i=1}^{n} f_{5i}^2 = \sum_{i=1}^{n} \Delta k_{d\,i} \cdot f_{5i} \qquad (3)$$

From operational reading was determined cumulative occurrences for each single cluster in each time period of technical mold life. These data serves as an input to the regression model, which create a knowledge base.

Created model was built and tested on real operational data, however specific results are not creator's ownership. For that reason it is not possible to present that results in that paper.

Created model further cooperates with solutions generator which is part of the expert system. This system will create a combinatory smelting sequence, which are tested with limiting conditions defined by user. By this way smelting plan is created which take into account technical state of the mold, blank's quality compliance and demanded production range.

Solution generator for planning expert system creates each single combinatory melting configuration, which are tested under limited conditions defined by user. [10]

3. CONCLUSION

Presented solution in form of mold's state regression model is a basis for new, still unpublished approach to operative control and production planning problems. The solution is intended to be applied on continuous steel casting devices with usage of conventional and non-conventional process modeling techniques.

Presented model allows to monitor mold's state in any time with help of analytical diagnostics. Also it can predict its state on the basis of scheduling production plan. The model is the base for expert planning system too, which performs support function for melting sequences planning.

Proposed model structure is applicable on various mold types and can solve another tasks from operative control area and product scheduling. In present time there are examined possibilities of usage presented model for sequences planning and minimizing mixed smelts, which can significantly increase efficiency on continuous steel casting devices.

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