Environment monitoring and sensor layers data integration in the production process of the electrosteel plant

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1. Introduction

Modern production systems consist of an increasing number of devices, most of which provide digital interfaces enabling access to information about the production process at individual stages of production. This feature is used in the concept of Industry4.0 systems, in which the real production process is mapped to a virtual model on which advanced methods of optimization and support of the production process can be applied [1]. A similar type of solution was presented in this work. Its main component enables monitoring the state of the technological process in the hall of the CMC Zawiercie electrosteel plant. This module is based on the integration of data from heterogenous sensor systems of the electrosteel plant and the component of visual detection of main ladles (MLs) from CCTV system. The work presents the general concept and main components of the system and the mechanism of its operation.

2. System architecture

A known problem in the production of steel products [2,3] and the main functionality of the solution implemented under this project is the optimization of the production process by maintaining the appropriate time and temperature parameters of this process, required to produce products in specific steel grades. Failure to meet such parameters by overheating or cooling down the charge or too much extension of the charge transport time in the main ladle (ML) on the way from the electric arc furnace (EAF) through the ladle furnace (LF) to the continuous steel casting station (CSC) makes it impossible to produce final products with specific parameters (steel grades).

The scheme of the system enabling the implementation of such functionality is presented in Figure 1 (a). One of the main components of this system is the metamodeling module which enables optimization of production volume and minimization of risk associated with a temperature. The optimization is performed by metamodel based on linear regression and neural network for the temperature drop which is occurring during the transport of liquid steel to the casting machine. The data on which the process optimization metamodel works comes from several heterogeneous data sources.

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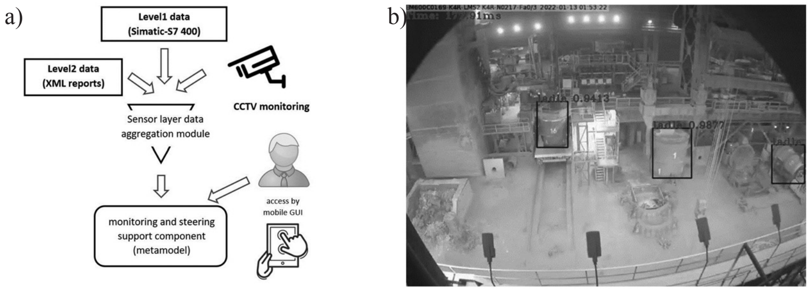

Figure 1. Overall system architecture (a) and main ladle (ML) detection module GUI (b).

These are: the sensor layer (Level1 and Level2 systems) and the ML recognition module operating on the basis of the CCTV system (Figure 1 b). The whole is aggregated by the sensory data integration component, enabling the implementation of two main functionalities provided by the system:

- Optimization of the production process (metamodeling component),
- Monitoring the status of the steelmaking process – based on mobile applications used by the staff.

2.1. Sensor layers

The two main sensory sources containing numerical data, on the basis of which the subsequent components of the system operate, are the Level1 and Level2 systems.

Level1 is a low-level hardware layer, integrated directly with the device controllers involved in the production process (EAF station, LF station, CSC station) which provides parameters (in real time) about the current state of these devices. Integration with this layer was based on the connection with Siemens Simatic S7 400 controller implemented by Sharp7 library, which is C# port of Snalp7 library. The data obtained from this layer include: the current temperature of the ML armor, the latest values of liquid steel temperature measurements, the current duration of the process at the EAF or LF station and the current amount of energy consumed at individual stations.

The Level2 system is another sensory layer of the steelworks hall, which provides data on the parameters of the process after the end of charge processing in the main ladle (ML) at individual stages of the production process (EAF, LF, CSC stations). This layer provides additional data on the production process regarding the entire production plan and a specific melt carried out in a given ML (grade, sequence in the production process, charge weight, chemical composition, oxygen and carbon content, total processing time on a given station, melting process efficiency) . This information is supplementary to the data from the Level1 system, however, it is not provided in real time, and appear in the system only at the end of ML processing at a particular station. Numerical data from the Level2 system is delivered in the form of XML file reports, which are detected and parsed using FileWatcher, xsd tools and standard C# libraries used to parse XML documents.

2.2. Vison processing

The image processing component performs two main functionalities - vat detection and identification of vat numbers. As part of the work on the vat detection issue, 4 different machine learning models were tested to check their effectiveness – Mask-RCNN, MobileNet, YOLOv3 and its tiny version. All were trained on a group of more than 8000 images where about 2000 were additionally modified with ImgAug tool. In addition, about 700 images of the electrosteel hall without MLs have been added. The test data was divided into the classic 80-training; 20%-validation sets. Two models were used in the problem of identifying the ladle number: pretrained CRAFT[4] and custom convolutional recurnet neural network. The results of the runtimes and vat detection efficiency are presented in Table 1. Python 3.10 and tensorflow 2.10 were used to implement the solution, and the models were built using the Keras library.

Table 1. Training and accuracy results of model used.

Parameter	Mask RCNN	MobileNet	YOLOv3	YOLOv3 tiny
Training time, h	6.32	3.57	2.51	0.89
Detection time CPU, ms	1 840	1 380	430	101
Detection time GPU, ms	680	450	173	37
Accuracy (typical position), %	96	95	94	92
Accuracy (overall), %	88	85	82	68

Vat detection performance at standard locations does not vary much between models. The difference starts to be visible only when atypical locations are taken into account (lower efficiency of the YOLOv3 tiny model). It has also been observed that the effectiveness of vat detection and identification of the vat number decreases slightly in situations where there is smoke or violent light flashes on the stage, which is a difficult case, because in such cases even the vision system operator has trouble recognizing the vat number.

2.3. Data aggregation component

Integration of data from various sensory layers (Level1, Level2, CCTV) is carried out in the system in the component that aggregates this data and makes it available to the optimization (metamodeling) and the process monitoring (by a mobile application) components. The exchange of information between these components is based on the open source message broker RabbitMQ. The component of monitoring the condition of the steelworks hall itself takes into account the accuracy and reliability of data from individual components in its operation. Data from the Level2 system have the highest priority (they are partially verified by the operator). They are then supplemented with data on the current state of the process provided from the Level1 layer (up-to-date data, but without information on the general state of the process). Data from the CCT system enable precise positioning of individual MLs within the entire hall (but they are the least accurate – there are situations of detecting a ML without recognizing its number or detecting a ML with an incorrect number). Adjustments to the ladle numbering are made based on data from the Level2 system, taking into account the sequencing of the ML processing scheme in the electrosteel hall.

3. Results and further works

As part of the presented works, an IT system was developed, which during the 18 months of operation (from the implementation phase of the prototype version) collected data on the production process in the steelworks hall. The currently collected data relate to: over 16 000 reports on melts at CSC, LF and EAF stations; number of temperature measurements: over 33 000 at the EAF, over 94 000 at LF stations, over 81 000 at CSCs; 58 000 tests of the chemical composition of steel, 75 different grades of steel. Currently, the system is in the phase of integrating its individual components, testing its effectiveness and implementing it to the production environment. Initial tests of individual components within the infrastructure tested in CMC Sp. z o. o. in Zawiercie (Poland) show that they work properly and can successfully support the process of continuous casting of steel carried out in the hall of the electrosteel plant of a given company.

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