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SIMULATION OF NEURAL AND FUZZY SYSTEM TO PREDICT, DETECT AND ELIMINATE CRACKS IN CONTINUOUS CASTING

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ABSTRACT: This paper work present Simulink implementation of a neural and a fuzzy system for prediction, detection and rejection of cracks in continuous casting processes. The neural and fuzzy system is made up by a neural network used for fissures detection and a fuzzy controller for predicting and rejecting them, who uses the signal from neural network and a part of data in the process to correct the casting speed and the primary cooling water.
KEYWORDS: Neural system, fuzzy controller, control, crack

❖ INTRODUCTION

Control systems [3] ensure the right working algorithms required by an appropriate system working- both technologically and generally speaking -, and also in case of classical systems based on PID numerical controller. Usually, there are no measures for crack prediction, thus rejects results from the process (in terms of tenth of tones of steel). In such case, working staff changes the working methods of the installation, based on internal instructions. The casting programmer is not appropriate and that has important economical implications [4].

Worldwide, there is research [1], [2], [5], [6], [7] who might lead to already-made crack detection (inside the crystallizing apparatus) and damaged goods. Currently used methods do not entirely eliminate the cracks; they are effective only if some features are being accomplished (crack detection at both exits of the crystallizing apparatus, a pretty slow phenomenon feature as far as the cracking correction is concerned etc.).

In [8], [9], [10], it is proposed a number of original solutions allowing the complete crack rejection from the cast material, outside the crystallizing apparatus. Therefore, it is designed a neural network [8] allowing us to detect any primary crack, by a thorough predictive analysis of the information received from a thermo-couple matrix. Information is used by a system based on fuzzy logics [10], which enables corrections of the casting speed and of the cooling water flow. Since this method does not lead to a complete crack rejection (although specialized literature refers to correcting the casting speed alone, in addition to that we have proposed to change the cooling water flow as well), we have adopted a new predictive principle who diminishes any possible cracking. Thus, the fuzzy system [10] analyzes a number of characteristic measurements and, although the neural network [8] has not yet acknowledged any crack, but it considers they may occur they perform casting speed corrections and cooling water flow occurs. Certainly, the solution we have proposed also implies a more complex fuzzy controller, using two sets of distinct set of rules [10].

❖ METHODOLOGY AND DISCUSSION - SYSTEM DESCRIPTION

To review the functioning of neural and fuzzy systems, we carry out the simulation in a Matlab-Simulink environment. Scheme implementation is given in fig.1.

BLOCK TEMPERATURE DATA GENERATION

In principle, we used recordings of the unfolding process. The best solution is to use two separate sets, one normal and one in case there is a crack. To switch between the two sets of data, we use a switch - control implemented in Simulink - Stateflow. Depending on a given parameter to the entry of this block, it switches between the two sets of data (1 - with crack, 0 – no crack). Block "CT Temperature" operate successively (every 120 s), the data "0" or "1", which basically makes the crack to occur or not. All data are memorized in „look-up data” tables.

NEURAL DATA PROCESSING BLOCK

We are able to identify any fissure if using data received from the 48 thermocouples mounted in 12 rows and 4 columns (on one side of the crystallizing apparatus). For each thermocouple, a dynamic neural network processes 10 consecutive temperature values. Any data received from a dynamic network is then processed by a space network who analyzes the values received from the two adjacent thermocouples. The input size value of such space networks (0 or 1) is introduced into a logical SAU (OR) block [9].

Figure 2 describes the connection amongst two dynamic networks and of a space network for data processing from two adjacent thermocouples.

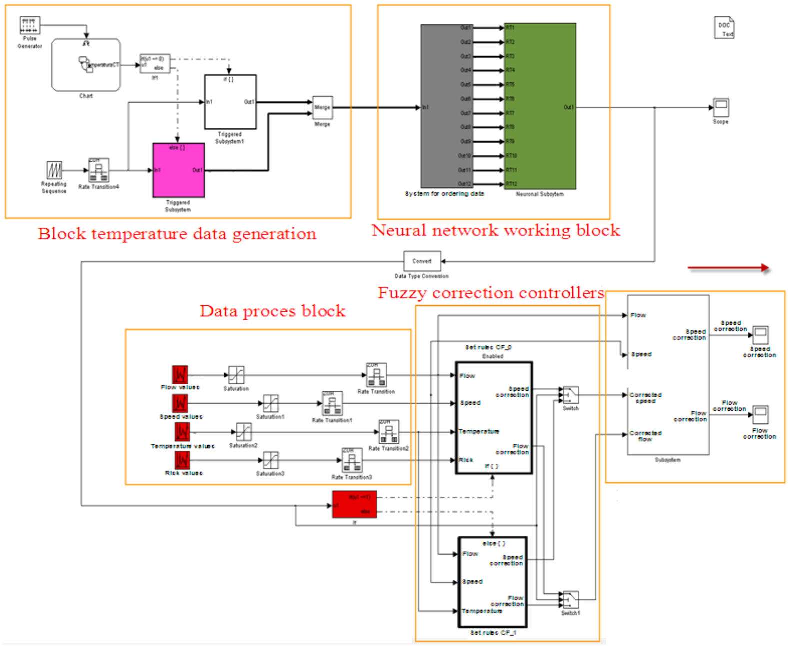

Fig. 1. Implementation in Matlab - Simulink of system

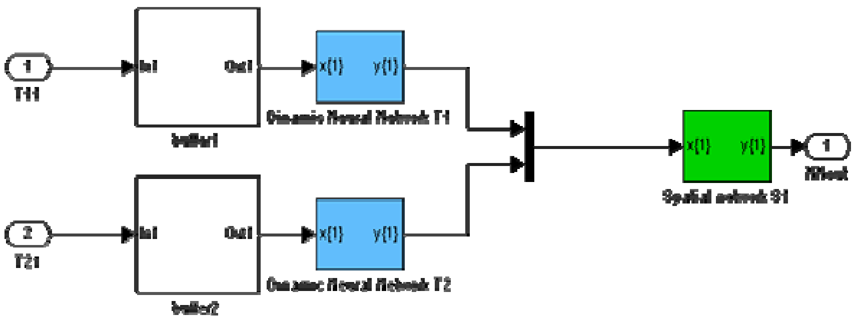

Fig. 2. Connecting two dynamic networks to space network for data processing from two thermocouples

According to the results of the logical SAU operation (we have analyzed output values of the space networks), when leaving the neural block we get a 0-value (there is no primary crack), and a 1-value (there is a primary crack).

FUZZY CONTROLLER (RG-F)

According to the value of the output value of the neural network, RG-F starts two different base sets: a corresponding base in case there are no cracks for „0” (225 rules), and a corresponding base in case there are some primary cracks (75 rules) [7]. The first set has four entries (casting speed, primary cooling water flow, distributor temperature, and technological risk). They are all read from the process (in real situations).

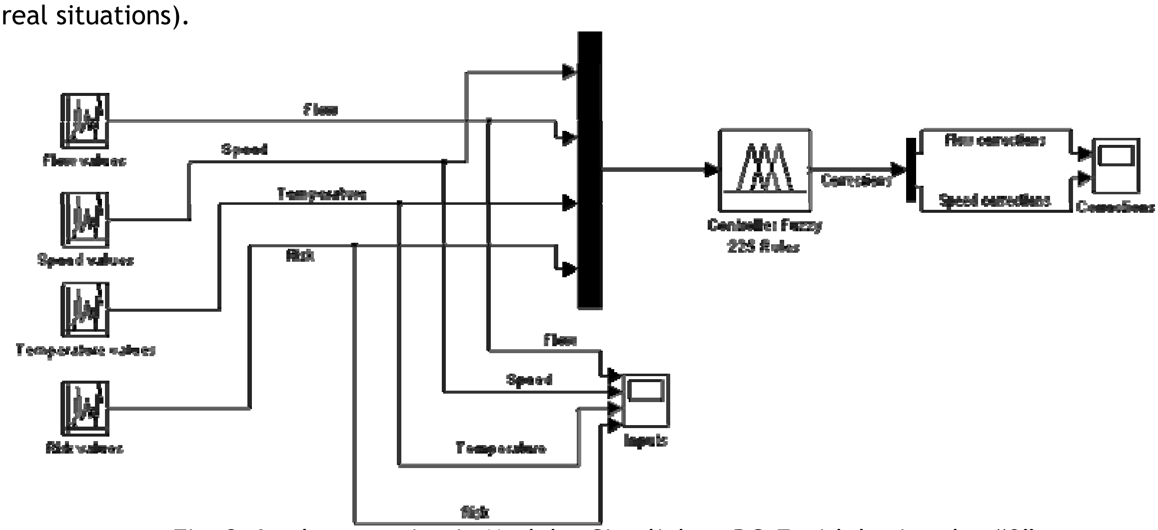

Fig. 3. Implementation in Matlab - Simulink to RG-F with basic rules “0”

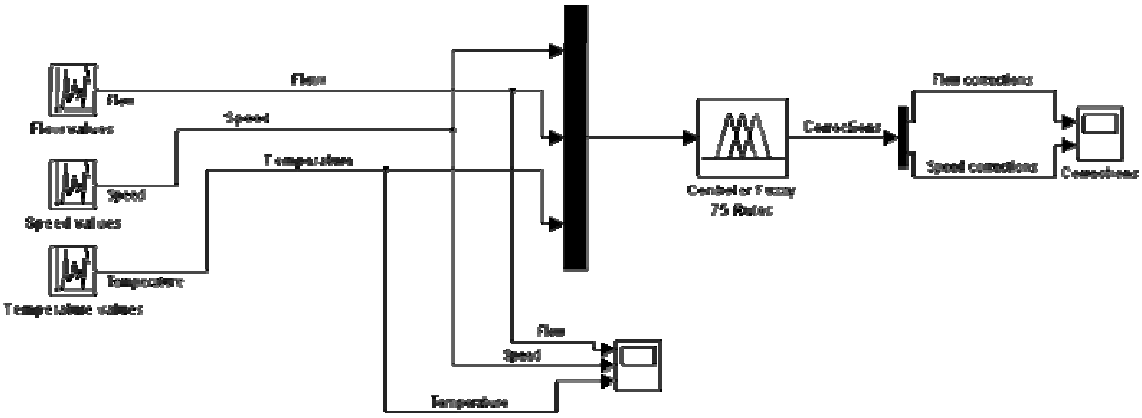

Fig. 4. Simulink implementation of the RG-F with basic rules "1"

We have used the „Process data block” to simulate it. The „technological risk” parameter is not necessary for the second set of rules, because its value is the highest since we have already detected some cracks. The two outputs of the RG-F (p_v - correction of speed, and p_q - correction of flow), are used for the limitation block [10]. Figure 3 describes the implementation of RG-F “0”, and in figure 4. we describe the implementation of RG-F “1” in the environment Matlab-Simulink.

Block prescribing

Block prescribing is replacing the values required for speed and flow (v *, q *), from the installation of automation existing in their new corrected values v_c, q_c), resulting in RG-F outputs. For simulation, the values v * and q * were considered equal to those measured sizes of the process (from "Block data processing").

❖ METHODOLOGY AND DISCUSSION - VALIDATION OF SIMULATED SYSTEM OPERATION

For validation of simulated system operation, for the entry fissures detection neural network we have applied two different sets of data measured during the current process and stored in tables. One of the sets refers to the situation when there are no cracks and the other one in case there is a crack. Neural network outputs reach 0 and 1 value and they show the network works correctly and it has detected the crack (in case they occur).

For each of the two cases generated at RG-F input, there are several input values (flow, speed, temperature, risk – if the neural network has produced a „0” output – there are no cracks or flow, speed, temperature; - if the neural network has produced an ”1” output value – there are primary cracks). These values are described in figures 5. and 6.: a) – time variation (120 seconds) of RG-F input values; b) – speed correction and new speed values; c) – flow correction and new flow values.

Figure 5. describes the situation during the first 30 simulation seconds, when the cooling water flow is low, the casting speed is low, the temperature inside the crystallizing apparatus is high, and the technological risk is low. Speed correction is very low, hence required casting speed is almost unchanged. During the next simulation 30 seconds, the technological risk increases, the fuzzy controller causes speed correction, and also avoids any crack (casting speed decreases). During the whole time, cooling water flow increases significantly. We can see that the other two simulation rounds are similar.

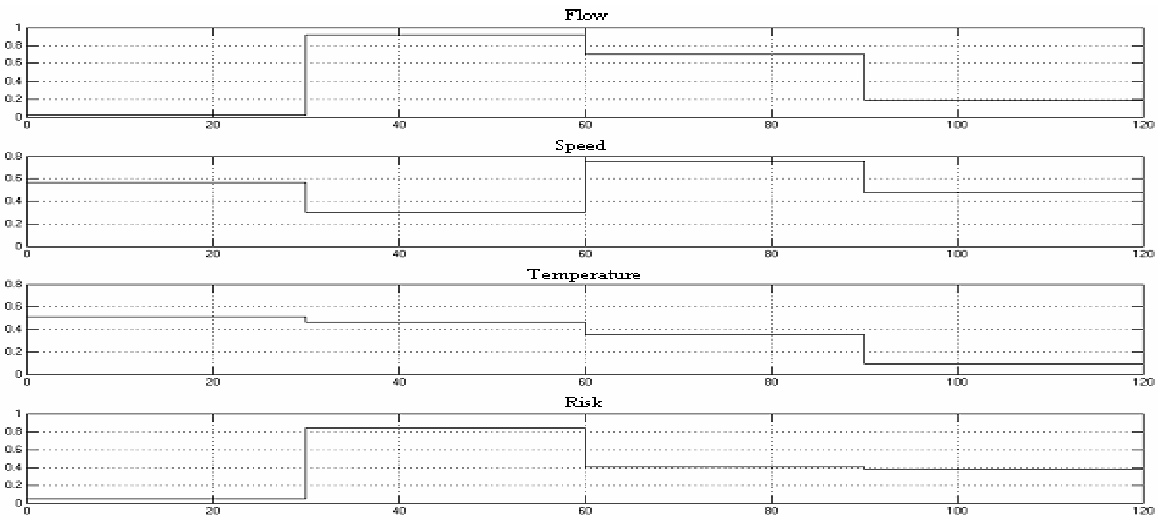

Fig. 5(a). RG-F Validation (RN=0) - RG-F Input Data

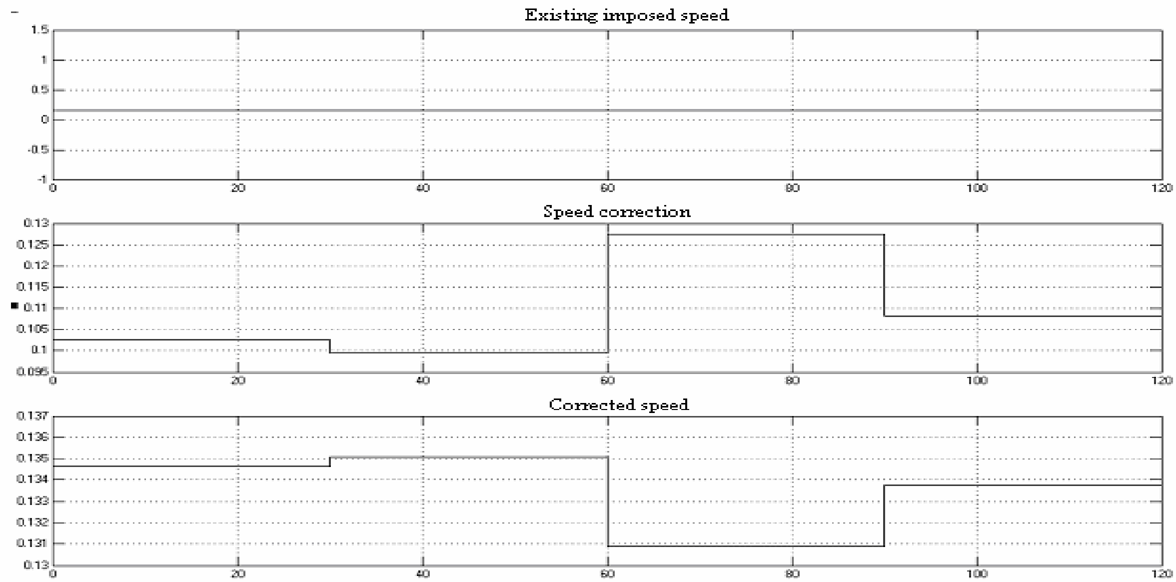

Fig. 5(b). RG-F Validation (RN=0) - Output data - speed

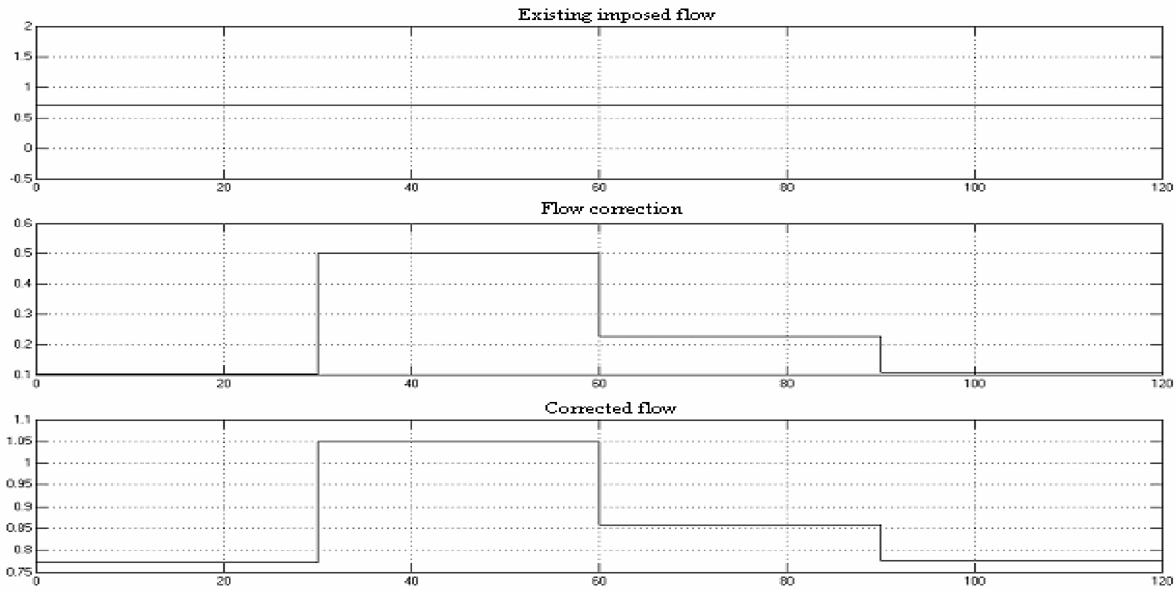

Fig. 5(c). RG-F Validation (RN=0) - Output data - flow

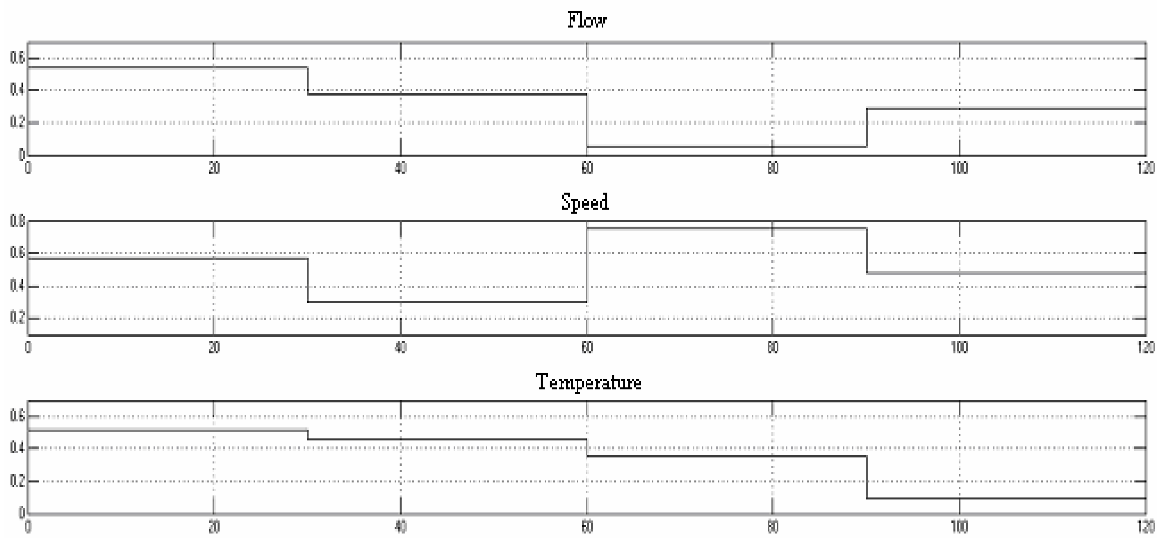

Fig. 6.a). RG-F validation (RN = 1) - RG-F input data

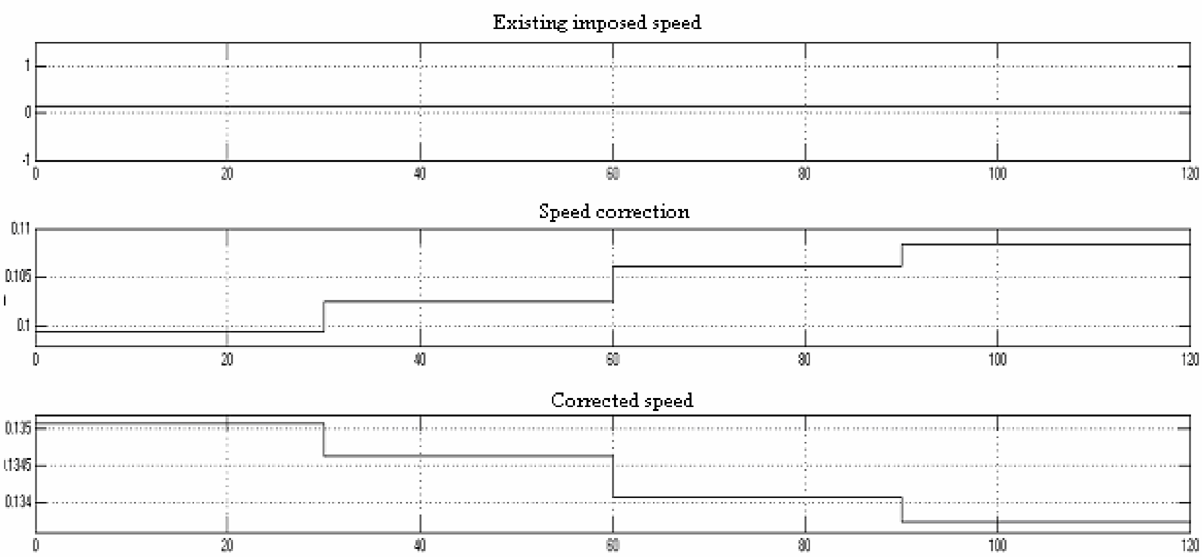

Fig. 6.b). RG-F validation (RN = 1) - Output data - speed

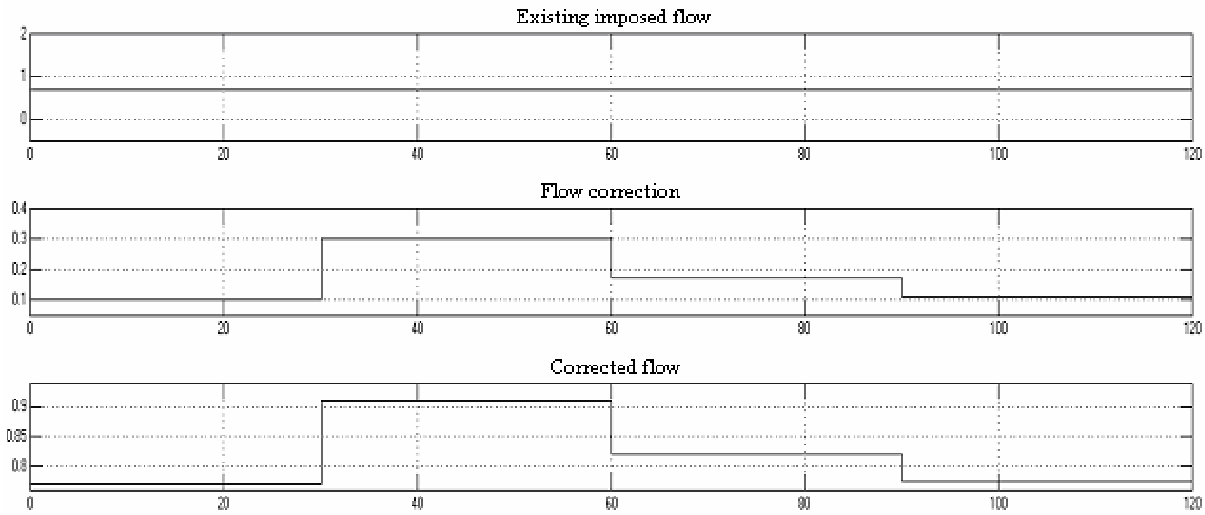

Fig. 6.a). RG-F validation (RN = 1) - Output data – flow

When analyzing all cases described in figures 5 and 6, we draw the following conclusions:

- ❖ RG-F analyzes the input values and elaborates speed corrections and water flow correctly, according to two base sets connected to each output of the neural network;
- ❖ Fore-writing block corrects all required values for speed and flow, according to RG-F outputs.

By simulating in Matlab-Simulink, we have proved that all solutions are correct – predicting, detecting, and rejecting any crack during continuous casting. Such simulation is made for performing a check out on the fuzzy system. During operation, all size values do not change so fast, hence some input values combinations are not that predictable. Once the system is implemented, the rules referring to such situations could be eliminated.

❖ CONCLUSIONS

We have performed a Matlab-Simulink simulation of the entire system. Considering this aspect, we have designed the simulation design and designed input sign generators, a neural network, a fuzzy regulator, and the fore-writing block for speed and flow values. When using this method, we have been able to use several input data sets, and the design has correctly generated all output values, acknowledging the whole system.

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