JMEPEG (1997) 6:599-604

Fuzzy Logic Modeling and Control of Steel Rod Quenching after Hot Rolling

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Reinforced concrete rod produced by European Community countries must comply with standards that establish minimum strength and tensile properties along with other technological and geometrical characteristics; however, possible variability within the assigned limits is not specified. Consequently, a number of manufacturing methods are now used, with the result that over time the mechanical properties of these products vary widely. Increased competition has led to the development of new procedures incorporating both process and quality control.

One example is a process based on the heat treatment undergone by the metal bars leaving the final stand of the rolling mill train. In this way, the mechanical and technological properties can be graduated, thereby enhancing strength (particularly yield point) without altering the deformability of the material. This procedure does away with the need to alter the chemical composition of the steel used to manufacture the rods. Process adjustment still relies on the experience of the production manager, however. This paper examines the possibility of applying fuzzy logic computer techniques to the heat treatment process in order to render it more rational and independent of operator unreliability.

Keywords fuzzy logic, quenching, reinforced concrete, self-tempering, steel rod

1. Introduction

In the European Community, the traditional production of steel rods for reinforced concrete has been influenced solely by the need to go beyond the limit values of certain mechanical characteristics while respecting other technological and geometric ones. This has led to the development of a number of different methods for manufacturing steel rods, ranging from the smelting of selected scrap to the purchasing of billets from different manufacturers to the rolling of products that would otherwise be scrapped.

Recently, however, the demand for products with guaranteed characteristics (for example, so-called weldable rod), increasingly stringent Community standards, and fierce competition from manufacturers in Eastern Europe have underlined the importance of process control in addition to conventional product control practices. Consequently, the time is now ripe for the problems associated with the manufacture of steel rods for reinforced concrete, traditionally regarded as an inferior product (and thus not worthy of any particular attention), to be tackled scientifically.

To obtain the required values for certain mechanical characteristics, a number of different methods are currently used, not all of them grounded on sound theoretical bases. For instance, alloying elements can be added to improve mechanical characteristics and supply other advantages, or a cold forming process can be introduced after hot rolling to harden the material and thus improve its mechanical properties (Ref 1, 2).

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However, the past few years have also witnessed the development of a new procedure based on a brief but intense heat treatment to which the rods are subjected on leaving the last stand in the hot rolling mill. This enables overall improvement of strength characteristics, especially yield strength, without excessive reduction of ductility. This technique has evolved considerably, although it has not entirely replaced the traditional process based on controlling the chemical composition of the steel produced (Ref 3, 4).

2. Innovative Technology for the Production of Steel Rods for Reinforced Concrete

The underlying principle of the innovative process outlined in this paper is to subject the rods to a controlled surface heat treatment on leaving the last stand in the hot rolling mill that will result in structural changes with increased strength properties, without an excessive loss of technological properties and ductility. Basically, the rod is passed through jets of pressurized water that cause a certain thickness of the steel to acquire a martensitic structure from what is effectively a quenching process, while the central part remains unaltered and maintains its austenitic structure. On leaving the rapid cooling section, the thermal gradient created in the bar causes the heat to radiate outward, thus inducing a self-tempering process in the martensite, while the core remains in its austenitic state. During the final natural cooling phase on the cooling plate, the residual austenite breaks down into ferrite and pearlite (Ref 5).

The final rod structure, identified by metallographic analysis and microhardness tests, will consist of the typical hardened and tempered structure in the outer ring, a normalized structure in the central core, and a mixture of the two in the interlying area (heat affected zone). It is thus possible to attain an overall improvement in strength characteristics (yield point and tensile strength) without reducing tensile properties, hence safeguarding rod ductility (Ref 6).

Thus, it is clear that the mechanical properties of the rod can be modified by changing the process parameters. Such an intervention makes it possible to adjust the extent of the treatment over a certain range (i.e., the thickness of the area treated) and consequently allows the desired properties to be obtained. Furthermore, this technique obviates the need to conduct a meticulous chemical analysis of the steel in order to obtain a rod of a certain diameter; nor, on the other hand, does a certain chemical composition necessarily have to be rolled to a particular diameter in order to ensure the desired mechanical characteristics.

If, in an initial approximation, we neglect the interlying transition area and consider the hardness as an index correlated to the strength characteristics (an acceptable hypothesis in the case of low-carbon steel), we can make a theoretical calculation, using the rule of ideal mixtures, to determine the tensile strength of the rod, which can be regarded as a sort of compound material with different characteristics in the core and in the outer ring. If we consider a rod of radius r and use the term H_e to indicate the hardness of the outer ring of thickness Δr, and H_i to indicate the hardness of the central core with a radius of $r - \Delta r$, the average weighted hardness of the rod will be given by:

$$H_m = H_e - (H_e - H_i)\left(1 - \frac{\Delta r}{r}\right)^2 \quad \text{(Eq 1)}$$

The mean hardness values calculated using Eq 1 and the estimated tensile strength, which differs from the true value by about ±15%, are reported in Table 1. The good agreement between the estimated values and those actually measured suggests the possibility of using a suitably calibrated form of the heat treatment process to obtain predefined mechanical characteristics without having to adjust the chemical composition at all.

In the heat treatment process in question, the mechanical characteristics of the rod depend on a number of variables that can be subdivided into two groups in terms of their effect on the production process: endogenous and exogenous. The first group includes preheating temperature, hot rolling sequence, chemical composition, and diameter of the rolled steel. The second group comprises such factors as the number of cooling sections active at the same time (i.e., the water flow rate), the speed with which the water is sprayed from the nozzles, and the rod transfer speed; in industrial plants the last parameter is predetermined for each rod diameter and thus will not be considered a modifiable process variable hereafter.

The following sections present observations regarding the influence that each of the main process parameters exerts on the final mechanical characteristics.

2.1 *Diameter*

Equation 1 immediately points out that, all other conditions being equal, varying rod diameter necessitates that proportional variations be made to the size of the area subjected to the heat treatment in order to ensure similar values for the mechanical characteristics. However, bearing in mind that the temperature at the end of the hot rolling process (about 950 °C) can keep the steel in the austenitic state but is not sufficient for recrystallization, the austenitic grain size, on which the fineness of the final ferrite-pearlite structure will depend, is greatly affected by the extent of the forming process, especially in the final rolling stands (Ref 5). Therefore, in order to obtain the same mechanical characteristics in rods of differing diameters, the area subjected to the heat treatment must increase more than proportionally with rod diameter.

2.2 *Chemical Composition*

Chemical composition, carbon content in particular, has a considerable influence on the mechanical characteristics of the steel. Such is its importance that in iron and steel industries using conventional technologies it is the only process variable that can be manipulated in order to obtain the mechanical and technological properties required for steel rods for reinforced concrete. The peculiar feature of the innovative technology considered here is that it allows chemical compositions to be largely neglected and tends toward production characterized by only slightly variable mechanical properties. It must be remembered, however, that as the carbon content increases, the layer subjected to heat treatment must be smaller and the cooling speed at the internal limit of this layer may be lower.

2.3 *Cooling Water Flow Speed*

The water flow speed in the cooling section spray nozzles predominantly affects the temperature profile obtained at the end of the production line, but does not substantially alter the temperature profile on the cooling plate. This clearly entails

Table 1 Results of microhardness tests

Diameter, mm	C_{eq}	Δr	HAZ(a)	HV_e	HV_i	HV_m	$\Delta r/r$	R_m
12	0.34	1.11	0.40	306	202	237	0.18	612
14	0.37	1.18	0.89	303	223	248	0.17	640
16	0.40	1.04	1.50	304	214	235	0.13	606
18	0.40	1.40	2.09	297	211	236	0.16	609
20	0.32	1.15	2.00	302	192	211	0.11	595
22	0.39	1.18	2.13	324	222	243	0.11	627
24	0.38	2.20	2.33	307	205	239	0.18	617
26	0.37	2.00	2.15	308	206	235	0.15	608
28	0.43	2.00	2.44	341	230	259	0.14	667
30	0.27	2.48	2.69	310	209	239	0.16	617

(a) HAZ, heat-affected zone

only a slight variation in the residual enthalpic content. Therefore, we can say that an increase in this parameter causes a reduction in the external temperature and a steeper temperature profile—that is, a greater cooling speed in the surface layers and a reduction in the thickness of steel subjected to the tempering treatment.

2.4 *Cooling Water Flow Rate and Number of Active Sections*

The water flow rate (i.e., the number of cooling sections in operation at the same time) significantly influences the temperature profile taken both at the end of the production line and on the cooling plate, although the effect on the latter is much more marked.

3. Experimental Results and Discussion

Steel rods used in improved-bond reinforced concrete are normally produced in a variety of different diameters and types according to their mechanical characteristics. The hot rolling process discussed here, whose salient characteristics are reported in Table 2, consists of a number of steps ranging between 18 for minimum-diameter rods (12 mm) and 10 for maximum-diameter rods (30 mm). The first four steps are performed in flat rolling stands, and the next steps are carried out in sizing rolling stands with formats and sections that can be varied according to the final diameter to be obtained.

Table 2 Characteristics of the continuous hot rolling plant(a)

Diameter, mm	No. of steps	ΔS_{tot}	v, m/s
12	18	99.33	16.0
14	16	99.09	16.0
16	16	98.81	12.5
18	14	98.49	10.0
20	14	98.14	8.5
22	12	97.75	7.0
24	12	97.32	6.0
26	12	96.86	5.5
28	12	96.36	4.3
30	10	95.82	3.8

(a) Production method: processing in electric arc furnace followed by continuous casting. Billet dimensions: 130 mm × 130 mm × 10 m. Billet preheating temperature: 1100 °C. Temperature at end of process: ~950 °C

The steel rod leaves the last rolling stand at a temperature of 950 °C and enters the treatment plant, where a series of nozzles set 0.5 m apart spray pressurized water around its entire perimeter. The area of rod affected by the jet of water depends on the water speed, the flow rate, and the pressure of the water before it reaches the nozzles. On passing through each of these sections, the steel rod undergoes a sudden cooling process, producing a forced film boiling mechanism. However, the enthalpic content does not actually change very much in the time it takes to get from one set of nozzles to the next, as the equidistant cooling sections are separated from one another in order to allow the water to flow away and to prevent it from coming into continuous contact with the steel rod.

In order to be able to determine in advance the mechanical characteristics that the steel rod will have after the treatment, we must know not only the cooling speeds reached in the various cooling sections so that we can determine the thickness of steel that may undergo transformations producing martensitic or bainitic structures, but also the residual enthalpic content when the rod leaves the cooling apparatus, which defines the extent of the self-tempering process in the treated area. As these two phenomena make it possible to determine the final structure and, therefore, the mechanical characteristics of the rod, a previous paper illustrated a numerical simulation of the two stages in the cooling process—namely, the forced film boiling inside the heat treatment plant and the process involving heat radiation and natural convection in the open air (Ref 6, 7).

The cooling process simulation was performed for all diameters and in various conditions of water flow from the nozzles and with varying numbers of cooling sections operating at the same time. Some results are shown in Table 3, where temperature on the cooling plate means the external temperature of the rod as it could be measured on the cooling plate about 30 m from the end of the plant; the latter turned out to be only slightly different from the core temperature, coinciding with the self-tempering temperature.

Further experimental tests performed at an industrial plant, which will be published in a subsequent paper, made it possible to determine that the mechanical characteristics in question are

Table 3 Cooling plate temperature for various process parameters

No. of cooling sections	Diameter, mm	Cooling plate temperature, °C				
		v = 20 m/s	v = 40 m/s	v = 60 m/x	v = 80 m/s	v = 100 m/s
5	12	822	787	763	746	733
10	12	733	681	651	631	617
15	12	657	598	567	549	536
20	12	591	530	501	485	475
5	20	829	799	780	767	756
10	20	752	709	685	670	659
15	20	686	638	614	600	590
20	20	630	580	558	545	537
5	30	805	776	758	746	738
10	30	723	685	665	653	646
15	30	656	616	597	587	580
20	30	600	560	545	535	529

defined by the temperature reached on the cooling plate when diameter and chemical composition are constant. Hence, the control problem consists of finding the possible combinations of water flow speed, water flow rate, and rod diameter that allow the desired temperature to be reached on the cooling plate.

Analysis of the results obtained using the simulation model together with the experimental measurements taken made it possible to assess the influence of the single modifiable process parameters, but this was insufficient to generate a complete model of the process in a closed form. However, a previous paper attempted a fuzzy logic approach to process control and obtained encouraging results, even if certain difficulties were encountered both in the definition of the fuzzy membership sets and in the writing of rules. Regarding the latter problem, the production rules must be sufficient in number to enable the correct definition of the problem without being redundant, and, above all, they must not conflict with one another.

4. Fuzzy Logic Model for Prediction of Optimal Temperature at the End of the Treatment

This paper, which in part stems from results already acquired, aims to use the Adaptive Neuro-Fuzzy Inference System (ANFIS) technique to search for the optimum form of the membership functions and to determine the rules needed to define the process using an adjustment procedure based on error backpropagation and a training data set (Ref 8, 9).

The first step is to identify the modifiable variables and to determine their effects on the mechanical characteristics of the rod. However, since it is not possible to develop a mathematical model of the process that will take into account all the variables in play and their reciprocal effects, this information and operator experience would normally have to suffice in order to select the process parameters to be used for process control. In light of this, a plausible solution is to address the possibility of using artificial intelligence techniques, such as fuzzy logic, in order to take the acquired knowledge into account without having to use a mathematical model or simulation techniques.

Fuzzy logic is a powerful yet straightforward technique that can help solve a variety of problems, especially in the field of process control and decision-making activities. Much of the inherent power of fuzzy logic stems from the possibility to draw conclusions and generate answers on the basis of information that may be inaccurate, ambiguous, incomplete, vague, or of a qualitative nature; such information can also be formulated as deduced linguistic expressions—for example, from the everyday experience of an operator who, in describing his or her own control strategy, may use constructs such as:

"IF x is equal to y, THEN w is equal to z"

The typical scheme of a control system based on fuzzy logic is shown in Fig. 1. The function of the first block is to associate the measured data, which assumes clearly defined values, with a fuzzy description using a device that could be called a crisp/fuzzy converter. The second block applies the fuzzy rules describing system behavior, while the third block is responsible for decoding the data and returning it in the form of exact values which can then be inputted to the control devices. The step between attribute description, achieved using natural language, and the description that is rigidly fixed by the syntactic rules needed for them to be processed is achieved using the theory of fuzzy sets. In this way, a value assumed by a characteristic, defined in its own domain (called the universe of discourse) is attributed with a degree of membership to a class by means of a function $\mu_A(x)$ that can assume a value (zero to one) and whose form must be established on the basis of personal experience and intuition.

The fuzzy sets can then be used to perform all the operations, as for the sets in Cantor theory, formally defined by Zadeh (Ref 10-12). Those most frequently used are conjunction, disjunction, and negation, whose definitions are given below.

The membership function of the conjunction C of two fuzzy sets A and B is defined as:

$$\mu_C(x) = \mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x))\ x \in X \text{ operation OR)}$$

The membership function of the disjunction C of two fuzzy sets A and B is defined as:

$$\mu_C(x) = \mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x))\ x \in X \text{ operation AND)}$$

The membership function of the complement or negation of the fuzzy set A is defined by:

$$\mu_{\not{C}A}(x) = 1 - \mu_A(x)\ x \in X \text{ (operation NOT)}$$

The basic problem arising from the use of a fuzzy controller is defining the classes to which the variables belong and finding an adequate group of rules to transform the fuzzy inputs into output values in the form of fuzzy sets. This mapping can always be expressed through fuzzy conditional relations; that is, a control rule can always be decomposed into a sequence of expressions of the type:

IF ... AND ... THEN ... AND ...

in which the statement following IF is called the antecedent and the one following THEN is called the consequent of the specific instantiation of the control rule.

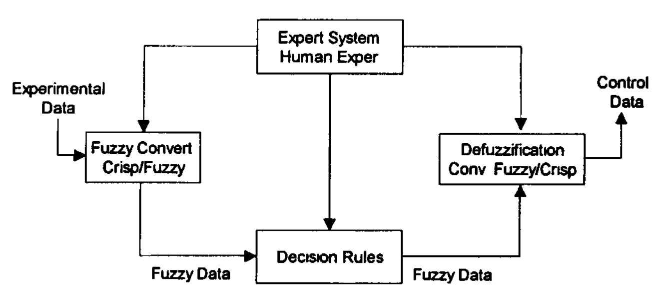

Fig. 1 Block diagram of a fuzzy logic controller

The degree of truth of the consequent can be determined using the correlation product inference procedure or the minimum correlation inference procedure, in which the membership functions of the consequents are truncated at the truth values of their relative antecedents (Ref 9, 13). In other words, all the rules are assessed at the same time using an OR operation; hence, the rule application method can be defined as a max-min type of procedure. The final stage in the decision-making process is the "defuzzification" procedure—that is, passing from the fuzzy sets of data in output to crisp values that can then be used as an input for process control. This is achieved by applying the center of gravity rule, which means evaluating a weighted mean value of the fuzzy sets produced:

$$\bar{x} = \frac{\int_D x \cdot \mu(x) \cdot dx}{\int_D \mu(x) \cdot dx} \quad \text{(Eq 2)}$$

Neural networks are now considered to be an important tool in the construction of membership functions and operations on these functions and in determination of the inference rules to adopt. In general, the construction of a neural network is based on learning patterns derived from consolidated experimental data. In order to give a rough outline of the process by which the membership functions are learned using a data set, let us consider a two-layer neural network with two inputs and one bias: the output layer with just one neurone ON_1, whose output Y gives the expected value T for each of the inputs X, and the hidden layer with m neurones $HN_1 \ldots HN_m$ connected both to the input neurones and the output neurones (forward network). The backpropagation algorithm is used to initialize the weights of the connections at random and with small values, then the output value Y is calculated for every X and compared with the desired value T. The weights are then updated on the basis of the global error and, at the end of the cycle, the total error is compared with a maximum allowed error, which constitutes the end of the learning process.

In the learning phase, it is necessary to use a training data set that contains the vectors of the inputs and the desired output. Furthermore, in order to check the generalization capability of the fuzzy inference system, it is worthwhile making provision for a checking data set to check system behavior. Figure 2 shows, with regard to cooling water speed, the trend of membership functions, both in the initial shape and as modified by the neuro-fuzzy method.

It must be remembered that the ANFIS learning technique uses the steepest descent gradient method for updating the parameters in the membership functions, and it is therefore possible for the learning phase to come to a premature ending if a local minimum in the objective function is reached. This drawback can be avoided by ensuring that the group of membership functions is fairly similar to the actual ones so that the algorithm can rapidly converge on the optimum solution in the parameters space. Operator experience and a profound knowledge of the process mechanisms are essential for definition of the initial set of membership functions.

To prevent network oscillation phenomena, it is advisable to define the learning rate updating strategy, which must be such as to ensure an increasing trend in the first learning phase up to a maximum value, followed by a gradual decrease toward the end of the learning process. This makes it possible to avoid a rapid learning process converging on local optimum values that are far from the absolute ones. On the other hand, in order to obviate the overfitting problem in the learning phase, a checking data set should be made available, especially when there are a large number of inputs and/or when the data are affected by noise. Virtually no attempts have been made to find a fuzzy inference system capable of ensuring an almost perfect adaptation to the training data, and most efforts are geared to the search for an inference system that, once the connections between the two input and output data structures have been learned, can then also be applied satisfactorily to the checking data—that is, to an area that has not been fully explored during the learning phase.

It must be pointed out that the weak point of this method, like other similar methods, lies in the combinatory explosion of rules if the size of the input variables vector is increased and if a large number of membership classes are considered for each of these variables. Therefore, it is worthwhile conducting a preliminary study in order to exclude the variables whose influence on the process is not considered to be fundamental.

In order to verify the validity of the ANFIS method with the proposed simulation model, the temperatures on the cooling plate were calculated for three diameters, five values of cooling

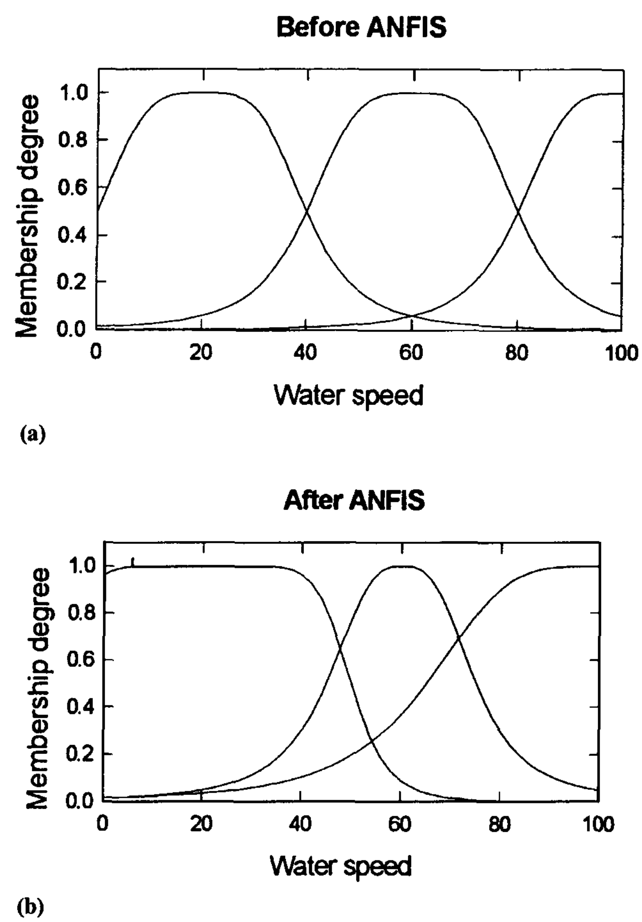

Fig. 2 Membership function shape modification by neuro-fuzzy technique

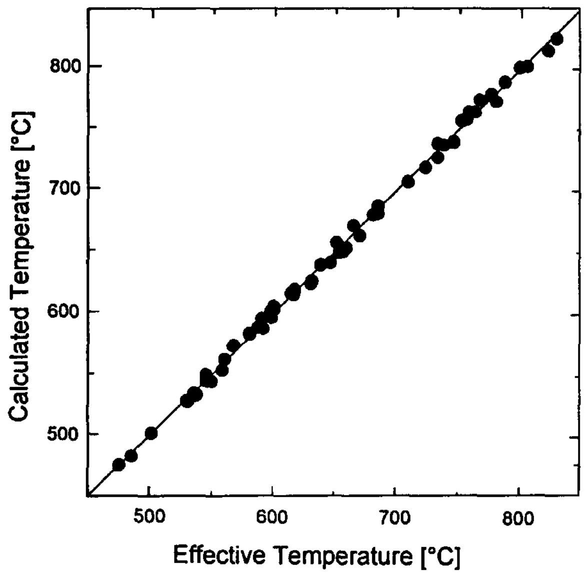

Fig. 3 Results of ANFIS technique versus actual values

water flow speed, and four values of the water flow rate, giving a total of 60 data items. As far as the membership functions are concerned, it was decided to use the bell form, with two fuzzy sets for the diameters, three for the cooling water speed, and four for the water flow rate. The two-level network with the backpropagation algorithm was trained using 59 data items in rotation for the learning process and the last one as a check. Figure 3 shows the values estimated by the fuzzy inference procedure as functions of the values calculated using the simulation model. A second experiment was carried out in which the fuzzy sets were generated while omitting the data for an intermediate value of each of the variables considered, in order to explore the generalization capability of the system. Here, too, the results can be considered satisfactory on the whole and point to the need to further investigate the method so as to make it possible to add other process variables that are currently held to be constant or that in any case do not greatly influence the temperature on the cooling plate.

Obviously, in an industrial context, the temperature values measured on the cooling plate may be significantly different from those calculated using the simplified theoretical model simulating heat exchange adopted in this paper. This can certainly be attributed to the difficulties encountered in determining the heat-exchange coefficients in the presence of film boiling phenomena. It must also be borne in mind that the actual heat-exchange surface is not a cylinder of diameter equal to the nominal diameter of the rod, as allowance must be made for tolerance levels and, more importantly, for the presence of protrusions that are typical of improved-bond products.

These considerations suggest that the neuro-fuzzy prediction model cannot be applied without first conducting a vast series of experiments to provide a sufficient set of data regarding various working conditions, which is needed for the system to be able to learn. It is equally clear that it is this very type of model, when suitably trained, that will make it possible to overcome the objective difficulties in predicting the actual temperature reached on the cooling plate at the end of the heat treatment.

5. Conclusions

By making use of experimental results and a simulation model for determining the temperature profiles that can be obtained in steel rods for reinforced concrete, it has been possible to verify that the mechanical characteristics of steel rods are closely correlated with the acquired structures, which in turn depend on the temperature reached after the sudden cooling and self-tempering treatment. However, the large number of variables in play makes it impossible to use a closed-form mathematical model to describe the dependences and interactions between the process variables and those of the material being processed.

Consequently, it was decided to verify the possibility of applying the fuzzy logic method to the process control. This has been tested with the aid of a simplified numerical model under the assumptions of constant temperature of the steel rod on leaving the last stand in the rolling mill and the same chemical composition of the steel used. Hence, the application examined has essentially regarded the choice of exogenous process parameters capable of ensuring the correct temperature on the cooling plate for each rod diameter.

The results obtained were, in any case, fairly satisfactory. In the future the same type of fuzzy logic will be used to determine the optimal self-tempering temperature on the basis of the chemical composition of the steel and the final diameter of the rod. In this way it will be possible to break free from the constraints imposed by the stocks available in the plant during production scheduling.

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