Abstract—A multivariable fuzzy system has been presented for higher level supervision of industrial process. With the help of a statistical process controller (SPC), this fuzzy supervisory control system can replace the human operator in the laminar cooling process. Since a feedforward compensator is designed to suppress the external disturbance, the proposed system can automatically find the proper operating points for the cooling process under the variation of boundary conditions. The values of control variables at the operating point will be taken as the setpoints of a distributed control system (DCS) in the relevant cooling mode. The simulation and practical experiment show the robust performance of the suggested system and its bright future in the industry.

Index Terms—Feedforward control, fuzzy control, laminar cooling process, multivariable control, statistical process control, supervisory control.

I. INTRODUCTION

In order to improve the metallurgical properties of the hot rolled slab, manufacturers usually use the laminar cooling system on the runout table to cool the slab from the austenitic finishing temperatures (820–900°C) down to the straightening temperatures (500–700°C) according to the slab thickness and the steel grade. Practically, the cooling process is controlled by the distributed control systems (DCSs), which are widely used in the metallurgical industry. The DCS-based process control can be classified into two levels, the local (lower) level and the higher level. The local level is to deal with the machine control using many control loops, including open loops and closed loops. Each control loop consists of a complete set of control components, such as, sensors, actuators, and controller. Since the control algorithms employed in local loops, such as PID control, auto-tuning control, predictive control, and fuzzy control, etc., are well developed, a satisfactory performance is always achieved in local loop. Even though the performance of each local loop is satisfactory, however, the overall performance of the process may not satisfy the manufacturing requirements due to the complexity of the process. The laminar cooling process is affected by many elements, such as, slab temperature, thickness and shape of the slab, the slab material, the temperature of water and environment, etc. All these factors are varying between different processes, and will be considered as boundary conditions of the slab.

In order to achieve the overall quality of the dynamic process, the higher level supervision and control is required to give the appropriate setpoints of local control loops according to the variation of environment and boundary conditions, and to drive the system to satisfy the production requirements. On the industrial site, however, this kind of supervision is handled by the human operator who unfortunately can only offer a coarse control. First, all boundary conditions that the laminar cooling process could have are classified into different groups, which are called operation modes in this paper. Through extensive experiments, a proper operating point is found for each operation mode. While in the cooling process, the values of control variables at the relevant operating point will be taken as the setpoints of DCS for the slab whose boundary conditions are matched. Since only one operating point is used for each operation mode that could have several different boundary conditions, the control accuracy will be limited by the operation mode classification. On the other hand, if the number of operation modes is more than what we can experiment, some operation modes have to rely on the interpolation or the human experience to obtain their operating points. This approximation may lead to the incorrect result and will cost more efforts and time.

Since the accurate mathematical model of this kind of process is hard to obtain [1]–[4], it will be extremely difficult for the conventional control theory (e.g., predictive control, optimal control) to control this cooling process well [5]. On the other hand, the intelligent control methods, like fuzzy logic system [6], [7], neural network [8], [9], and knowledge engineering [10], [11], have been applied to control the complex industrial processes due to their loose requirement on the process model, and their capability to use the human experience. Therefore, these intelligent methods are suitable to set up the process control model to control the laminar cooling process, and to finish the task of coarse control which is usually proceeded by the human operators.

This paper presents a systematic approach to develop a hybrid fuzzy/statistical multivariable control system with a feedforward compensation for the laminar cooling process. This hybrid system can replace the human operator by auto-searching the proper operating points for the cooling process under variations of boundary conditions. The system consists of a dominant multivariable fuzzy supervisory control system to simu-
late the human decision making, a statistical process control (SPC) mechanism to simulate the human perception of input signals. With the help of a feedforward compensator to eliminate the variation of boundary conditions, the fuzzy supervisory control system can successfully find the proper operating point of each operating mode, then the setpoints of DCS for lower level control can be determined. The successful demonstration of the proposed intelligent system in both simulation and real experiment confirm the viability and effectiveness of the methodology.

II. LAMINAR COOLING SYSTEM

A. System Description

The process with the water curtain cooling system is simplified in Fig. 1. The runout table is 126 m long from the mill to the straightener, and the water-cooling zone is 26 m long. Four infrared pyrometers \(T_1 - T_4\) are mounted on the top of the runout table to measure the top surface temperature of the slab at the exit of mill, the entry of cooling area, the exit of cooling area, and the entry of the straightener. Two pyrometers \(T_1'\) and \(T_3'\) are mounted on the bottom of the runout table to catch the bottom surface temperature of the slab. One X-ray gauge \(D_1\) is located at the exit of the rolling mill. The cooling area is partitioned into three sections, labeled A, B, and C. The temperature drop is caused by the heat radiation only in section A and C, but by both radiation and water cooling in section B.

Thirteen cooling units are uniformly spaced along section B to implement two principle models of heat transfer [12], radiation losses and the water cooling. Each cooling unit consists of a water curtain on top of the slab and two spray headers on bottom of the slab. In order to ensure the accurately temperature control and the uniform heat dissipation on both top and bottom surface, the cooling units on top and bottom of the slab can be activated simultaneously or separately, and furthermore, their water flow rate \(\gamma\) (bottom water flow/top water flow) can be adjusted separately.

B. Model of the Heat Loss

1) Model of Heat Radiation: The heat loss due to radiation can be modeled by the following equation [13]:

\[
\frac{dT}{dt} = \frac{8\kappa A_r}{\rho(T)c(T)V} \left[ (1.8T + 492)^4 - (1.8T_e + 492)^4 \right]
\]

where

- \(T\) material temperature in °C;
- \(T_e\) environment temperature in °C;
- \(\kappa\) Stefan Boltzman constant;
- \(\varepsilon\) emissivity;
- \(A_r\) surface area subjected to radiation;
- \(\rho\) specific density of rolled material;
- \(c\) special heat of the rolled material;
- \(V\) volume of the body.

Integrating (1) over radiation time from zero to \(t_{raditions}\) yields the expression for temperature loss via the radiation

\[
\Delta T_{raditions} = \frac{8\kappa A_r}{\rho(T)c(T)V} \left[ (1.8T + 492)^4 - (1.8T_e + 492)^4 \right]
\]

2) Model of Water Cooling: Fourier equation in the conduction theory is used as the water cooling model in (3)

\[
\frac{\partial T}{\partial x} = \frac{\partial}{\partial t} \left( \lambda \frac{\partial T}{\partial x} \right)
\]

where \(0 < x < H\) and time \(\tau > 0\). The boundary conditions are

\[
\begin{align*}
-k_0 \frac{\partial T_0}{\partial x} + \alpha_0 T_0 &= \alpha_0 T_w \quad x = 0, \tau > 0 \\
k_N \frac{\partial T_N}{\partial x} + \alpha_N T_N &= \alpha_N T_w \quad x = H, \tau > 0 \\
T &= \phi(x) \quad 0 \leq x \leq H, \tau = 0
\end{align*}
\]

where

- \(\lambda\) thermal conductivity (W/m°C);
- \(k\) thermal diffusivity (m²/s);
- \(H\) slab thickness (mm);
- \(T_w\) water temperature (°C);
- \(T_0, T_N\) bottom and top surface temperature (°C);
- \(\alpha_0, \alpha_N\) bottom and top surface transfer coefficient (W/m² · °C);
- \(\phi(x)\) function of initial conditions.

For this particular case, the transfer coefficient \(\alpha\) has the following formation:

\[
\alpha = b_x \times \frac{W_{by_0} - b_0 T}{T_{by_0}} \times (1 - b_0 T_w) \times \psi_{by_0}
\]

Fig. 1. Schematic diagram of the water curtain cooling system.
where \(b_1-b_6\) constant coefficients; 
\(v\) speed of runout table (m/s); 
\(W_p\) represents the spraying strength of cooling water to slab in the following format:
\[
W_p = \frac{Q_w}{w \times \Delta l}
\] (6)

where 
\(Q_w\) water flow of one top cooling unit (m\(^3\)/h); 
\(w\) slab width; 
\(\Delta l\) distance of two neighbor cooling units.

Though the water cooling model presented in this section is only a good approximation of the real cooling process, however, it shows the complexity of the cooling process and provides a good base for the simulation.

C. Operation Modes, Boundary Conditions, and Temperature Errors

In the cooling process, the operation mode is defined by steel grade, thickness \(d\), and the final cooling temperature \(T_c\). For example, for the low-carbon steel (0.23%C), if the thickness is classified in interval of 2 mm, then there are 15 groups in total for the slab with thickness 10–40 mm; moreover, if there are five desired final cooling temperature \(T_a\), then the total operating modes for this low-carbon steel is 75 (15 \(\times\) 5).

In any operation mode, main entry boundary conditions for the slab to move into the cooling area are the thickness \(d\), detected by X-ray gauge \(D_1\), and the temperature \(T_{in}\) measured by the heat pyrometer \(T_2\). These two boundary conditions can be regarded as measurable disturbances and have much influence to the cooling process. Other boundary conditions will be treated together with other internal changes in the cooling process as small disturbance and expressed as an unobservable vector \(\Omega_\ast\), which includes

- the temperature deviation between the bottom and top surface of the slab \(\Delta T_{\text{bd}}\) before pyrometer \(T_2\);
- the temperature difference between head and end of the slab \(\Delta T_{\text{he}}\) before pyrometer \(T_2\);
- the temperature variance of water \(\Delta T_w\);
- the temperature variance of environment \(\Delta T_{e}\);
- the small changes of the slab’ shape;
- the physical/chemical reaction in the slab itself.

After one slab cooling is finished, there is still a temperature difference between head and end of the slab \(\Delta T_{\text{he}}\) since the whole slab can not move into the cooling area simultaneously. Because of slab thickness (10–40 mm) and the different cooling capacity, there is also temperature difference between the bottom (down) and top (upper) surface of the slab \(\Delta T_{\text{du}}\). These two temperature difference need to be measured at Pyrometer \(T_3\) or \(T_4\), and controlled.

D. Control Targets

According to the above analysis, four control targets need to be controlled for the cooling process:

- the temperature loss rate \(V_r\) caused by water cooling;
- the final cooling temperature \(T_{cm}\) measured by pyrometer \(T_4\);
- the temperature deviation \(\Delta T_{\text{bd}}\) between bottom (down) and top (upper) surface of the slab at pyrometer \(T_3\);
- the temperature difference \(\Delta T_{\text{he}}\) between head and end of the slab at pyrometer \(T_4\).

1) Off-Line Adjustment: At each operation mode, the loss rate \(V_r\) is relatively constant and defined by the technical requirement as follows:

\[
V_r = \frac{\Delta T}{\Delta L} = \frac{\Delta T}{\Delta L} v
\] (7)

where
\(\Delta T\) temperature drop (°C) caused by cooling water;
\(\Delta t\) time period for the slab staying in the cooling area;
\(\Delta L\) length of the cooling area;
\(v\) speed of the runout table.

In general, \(\Delta T/\Delta L\) is relatively constant. Since the speed \(v\) can be defined prior at each cooling mode, \(V_r\) can be determined off-line instead of on-line.

2) On-Line Control: The initial temperature \(T_{in}\) drops to \(T_{\text{rad}}\) due to the cooling water, and further to \(T_{cm}\) due to the radiation. The temperature loss of radiation is expressed as

\[
\Delta T_{\text{rad}} = T_{\text{rad}} - T_{cm}\] (8)

Substituting (8) into (2) with \(T = T_{\text{rad}}\). \(T_{\text{rad}}\) can be calculated. On the other hand, \(T_{cm}\) can be approximated as \(T_{\text{rad}}\) by neglecting the effect of radiation.

Through the physical analysis, the control law can be figured out as

- \(\Delta T_{\text{he}}\) can be reduced by accelerating the runout table \(a_{(\text{mm}/\text{s})^2}\);
- \(\Delta T_{\text{du}}\) can be eliminated by adjusting the flow rate \(\gamma\) (bottom water flow/top water flow);
- \(T_{cm}\) can be controlled by the number of opening cooling units \(N\) and the water flow of one top cooling unit \(Q_w\).

However, the strong nonlinear coupling between control variables makes the above control much more difficult.

E. Operation Model of the Cooling Process

The laminar cooling process in Fig. 1 can be divided into two subprocesses, the uncontrollable model \(P'\) and the complex model \(P\) as shown in Fig. 2. The measurable disturbance \(\Delta T_{\text{in}}\) and \(\Delta d\), referring to the variance of slab entry temperature and thickness compared to the previous one, influence the cooling process through the model \(P'\). The unmeasurable disturbances \(\Omega_\ast\) affect the cooling process through the model \(P\).

To eliminate the influence of the boundary variations, a supervisory control system is required on the higher level to determine the correct setpoints of DCS control variables \(a, \gamma, N,\) and \(Q_w\) under disturbances \(\Delta T_{\text{in}}, \Delta d,\) and \(\Omega_\ast\), so that the process outputs \(T_{cm}, T_{\text{du}},\) and \(\Delta T_{\text{bd}}\) can satisfy the desired requirement after the cooling process. The steel grade, thickness \(d\), desired final cooling temperature \(T_c\), and control variables \(v, a, \gamma, N,\) and \(Q_w\) compose an operating point for one cooling mode. The control variables \(v, a, \gamma, N,\) and \(Q_w\) in this operating point are setpoints of DCS \((a_0, a_0, \gamma_0, N_0,\) and \(Q_{\text{w}0})\) for a coarse control of cooling process.
In manufacturing site, the supervisory control is operated by human experts, who determine proper setpoint values for control variables through several typical experiments and a period of manufacturing operation. The control procedure can be summarized as:

1) to obtain and process the datum from a number of typical experiments;
2) to establish the adjustment relation between the control variables and the controlled errors, and the internal relations between control variables, according to previous experience;
3) to determine a proper sequence for regulating.

The operation of the DCS controlled cooling process with human supervision is schematically illustrated in Fig. 2.

III. HYBRID FUZZY/STATISTICAL MULTIVARIABLE CONTROL SYSTEM WITH FEEDFORWARD COMPENSATION

If the boundary conditions can be maintained to be invariant, i.e., with disturbances $\Delta T_{in}$ and $\Delta d$ eliminated, then the proper operating point will be found after a small number of slab cooling trial. Unfortunately, in manufacturing site, many disturbances (measurable or unmeasurable) exist and make it very difficult for operator to obtain the proper operating point. To improve the reliability of the supervisory system, the automatic control system is required. Since the laminar cooling process is a multivariable control system with the extremely complex properties, consisting of the uncontrollable process $P'$ and the unmodeled process $P$, the conventional control methods are not suitable for this higher level control. On the other hand, intelligent technologies will be a good candidate for this unmodeled process. The experience and knowledge of the human operator provide a good qualitative model for the supervisory system, which can easily be imitated by the fuzzy system. Since the technical indexes $T_{cm}$, $\Delta T_{du}$, and $\Delta T_{hw}$, upon which human operator make a decision, are statistical values, an SPC is necessary to generate these statistical values. Moreover, to suppress variations of the boundary conditions, the feedforward compensator is useful to assist the operator in decision making.

The supervisory control system that replace the human operator is actually a hybrid fuzzy/statistical system with one auxiliary compensation, which is outlined as below and illustrated in Fig. 3:

1) an SPC system to simulate the human perception of input signals;
2) a fuzzy multivariable control system to simulate the expertise and knowledge of a human operator;
3) a feedforward control system to compensate the effects of the variation of boundary conditions.

A. Feedforward Compensator

Two main boundary conditions that can be measurable and cause significant process variations are $T_{in}$ and $d$. The variance between the current slab and the previous one $\Delta T_{in}$ and $\Delta d$ are major disturbance for the compensator to suppress as shown in Fig. 3

\[
\Delta T_{in} = T^2_{in} - T^1_{in}, \quad \text{and} \quad \Delta d = d^2 - d^1
\]

with $T^1_{in}$ and $d^1$ refer to the entry temperature and thickness of the previous slab; $T^2_{in}$ and $d^2$ refer to the entry temperature and thickness of the current slab.

The other small disturbance $\Omega_\delta$ can be neglected based on the assumptions of the robustness of the dominant fuzzy control system [14].

The physical analysis [15]–[17] and extensive simulation show that the model of the feedforward compensator can be developed as follows:

\[
\Delta N^r = \alpha_c \frac{T^4_{in} \Delta d + d^4 \Delta T_{in} + \Delta T_{in} \Delta d}{Q_{e0}} N_0
\]

\[
\Delta N^f = \text{INT}(\Delta N^r + 0.5)
\]

\[
\Delta d^f = \frac{\Delta N^r - \Delta N^f}{N_0 + \Delta N^f} Q_{e0}
\]

where $\alpha_c$ is a constant coefficient, INT is an integer function.
B. Statistical Process Control (SPC)

The final cooling temperature $T_{cm}$, and the temperature deviation $\Delta T_{be}$ and $\Delta T_{du}$ that the operator perceives from the experiment is of moving average features. Therefore, these variables should be processed statistically as below before feeding into the dominant fuzzy control system

$$
\begin{align*}
T_{cm} &= \frac{\sum_{i=1}^{K} T_{4(i)}}{K} \\
\Delta T_{be} &= 2 \left( \frac{K/2}{\sum_{i=1}^{K/2} T_{4(i)}} - \frac{K}{\sum_{i=K/2+1}^{K} T_{4(i)}} \right) / K \\
\Delta T_{du} &= \frac{\sum_{i=1}^{K} (T_{4(i)} - T_{3(i)})}{K}
\end{align*}
$$

where $T_4$, $T_3$, and $T_3$ refer to the temperature detected at the corresponding pyrometer and $K$ is the number of the samplings.

C. Multivariable Fuzzy Supervisory Control System

The human operator adjust the setpoint variables of DCS ($\gamma$, $a$, $N$, $Q_e$) via four process variables $d$, $\Delta T_{du}$, $\Delta T_{be}$, and $\Delta T_{cm}$. This supervisory control requires a four-input/four-output fuzzy system to simulate the decision making of the human operator. This high-dimensional fuzzy system is very difficult to construct as well the couplings between setpoint variables.

Through the theoretical analysis and extensive simulations, the dominant relationship between process variables and the control variables has been figured out as in Table I. The thickness $d$ of the slab is only an auxiliary parameter to affect the cooling temperature. This multivariable process can be considered as four dominant loops with couplings between the setpoint variables. The multivariable fuzzy control system can be designed based on the following two steps.

1) Design a conventional fuzzy controller for each dominant loop.

2) Design a decoupling mechanism to suppress the coupling between loops.

In Fig. 4, four dominant fuzzy logic controller are $F_\gamma$, $F_a$, $F_N$, and $F_Q_e$ for controlling four setpoint variables: $\gamma$, $a$, $N$, and $Q_e$ according to input variables $d$, $\Delta T_{du}$, $\Delta T_{be}$, $\Delta T_{cm}$. When one loop is operating in the isolated situation (other loops are not in operation), the interaction from other loops is minimal. The fuzzy inference system will be relatively easy to design. Since the fuzzy inference system is used to search for the proper setpoint of DCS, PI type fuzzy controller [18] is suitable to eliminate the steady-state error. Each inference mechanism is configured as in Fig. 5, using standard triangular membership functions. The rule base for each inference engine, extracted from the fundamental mechanism of the process and knowledge of operators, is shown in Table II and Table III.

Through the fundamental analysis and extensive simulation, the coupling between loops can be obtained and classified into two different types in the laminar cooling process.

1) Coupling between $N$ and $Q_e$:

Variables $N$ and $Q_e$ are not adjusted simultaneously because they control the same target $T_{cm}$; on the other hand, $N$ is for large and coarse adjustment, and $Q_e$ for fine adjustment.

2) Coupling between variables ($\gamma$ and $a$) and ($N$ and $Q_e$)
   - The variations of $\gamma$ and $a$ have significant impact to the performance of $N$ and $Q_e$. When moving speed
of the slab and water flow rate change, not only change $\Delta T_{da}$ and $\Delta T_{he}$ effectively but also varies $T_{cm}$ greatly.

* On the other hand, variations of $N$ and $Q_e$ have little influence to $\gamma$ and $\alpha$. When $T_{cm}$ changes, $\Delta T_{da}$ and $\Delta T_{he}$ may change slightly.

The basic strategy for the human operator to achieve a decoupling control can be described as follows.

1. **First, the variable $\gamma$ and $\alpha$ should be tuned to eliminate $\Delta T_{da}$ and $\Delta T_{he}$.**
2. **After obtaining satisfactory $\Delta T_{da}$ and $\Delta T_{he}$, the final cooling temperature $T_{cm}$ will be controlled by adjusting $N$ and $Q_e$, by which $\Delta T_{da}$ and $\Delta T_{he}$ have little changes.**

The human strategy for decoupling control can easily be developed via three following rules, which simplifies the high-dimensional multivariable fuzzy system. If the coupling is more complex, the more advanced strategy can be implemented in the similar way.

1. **Coarse adjustment**
   - If $\Delta \gamma$ or $\Delta \alpha$ is relatively large (PL, PB, PMB, PM, NM, NMB, NB, NL), or $\Delta T_{cm}$ is big (PL, PB, NB, NL), then start the inference $F_{\gamma}$ to adjust $\gamma$.
2. **Fine adjustment**
   - If $\Delta \gamma$ and $\Delta \alpha$ is relatively small (PMS, PS, PZ, NZ, NS, NMS) and $\Delta N$ is zero, then start the inference $F_{Q_e}$ to adjust $Q_e$.
3. **Regular adjustment**—Stop inference $F_{N}$ and $F_{Q_e}$ in other circumstances.

Since the fuzzy rules are normally extracted according to one type of steel grade (e.g., low-carbon steel 0.23% C) or the ones that are close to the low-carbon steel. If the physical property of the steel $k$ (thermal diffusivity) and $c$ (special heat) change largely, the derived fuzzy rules may not work well. It is known from the heat transfer theory that the thermal diffusivity $k$ can reflect the heat conduction capacity of the steel, therefore, an adaptive factor $\eta$ is used to adjust the inference results in equation (13)

$$\eta = \frac{k_0}{k}$$

where $k$ is the thermal diffusivity of any steel grade, and $k_0$ is the one upon which the fuzzy rules are designed.

### IV. SIMULATION AND INDUSTRIAL EXPERIMENTS

The proposed multivariable fuzzy supervisory control system has been tested through simulation and industrial experiments. The simulation models are described in Section II-B, and the results can satisfy the manufacturing requirements. Table IV gives the common boundary conditions of the slab in the simulation and the real experiment. As discussed previously, first six variables in the table $T_{cn}$, $T_{cm}$, $T_{in}$, $T_{he}$, $T_{da}$, and $T_{he}$ are either measurable or unmeasurable boundary conditions, which are disturbances to the process. The last three variables in the table $T_{c}$, $\Delta T_{cn}$, and $\Delta T_{da}$ are control requirements. When all these three requirements are satisfied, the searching for proper operating points will be finished.

Simulations in Fig. 6 show that the fuzzy supervisory control system is able to obtain the proper operating point through only four slabs. Under the varying environment with the variation of the heat transfer coefficient $\alpha$, i.e., the changes of the properties of the cooling equipment, the fuzzy system can also find the operating point. Simulations in Fig. 7 show the importance of the adaptive factor $\eta$ when the steel grade changes.

The real experiments in Fig. 8 show that eight steel slabs are required to obtain the proper operating point for low-carbon steel, and 11 slabs for Manganese steel. These industrial experiments confirm effectiveness of the proposed supervisory system.
TABLE II
RULE BASE FOR ADJUSTMENT OF $d r / \Delta T_{dw}, d k / \Delta T_{hw}, d N / \Delta T_{cm}$

<table>
<thead>
<tr>
<th>$\Delta T_{dw}, \Delta T_{in}, \Delta T_{cm}$</th>
<th>HZ</th>
<th>MS</th>
<th>HMS</th>
<th>HM</th>
<th>HMB</th>
<th>HB</th>
<th>HL</th>
</tr>
</thead>
<tbody>
<tr>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
</tr>
<tr>
<td>NB</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
<td>NB</td>
</tr>
<tr>
<td>NM</td>
<td>NL</td>
<td>NL</td>
<td>NB</td>
<td>NB</td>
<td>NMB</td>
<td>NMB</td>
<td>NMB</td>
</tr>
<tr>
<td>NS</td>
<td>NMB</td>
<td>NMB</td>
<td>NMB</td>
<td>NM</td>
<td>NMS</td>
<td>NMS</td>
<td>NMS</td>
</tr>
<tr>
<td>NZ</td>
<td>NMS</td>
<td>NMS</td>
<td>NMS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
<td>NS</td>
</tr>
<tr>
<td>PZ</td>
<td>PS</td>
<td>PS</td>
<td>PS</td>
<td>PS</td>
<td>PZ</td>
<td>PZ</td>
<td>PZ</td>
</tr>
<tr>
<td>PS</td>
<td>PM</td>
<td>PM</td>
<td>PMS</td>
<td>PS</td>
<td>PS</td>
<td>PS</td>
<td>PS</td>
</tr>
<tr>
<td>PMS</td>
<td>PMB</td>
<td>PMB</td>
<td>PMS</td>
<td>PS</td>
<td>PS</td>
<td>PS</td>
<td>PS</td>
</tr>
<tr>
<td>PMB</td>
<td>PB</td>
<td>PB</td>
<td>PM</td>
<td>PM</td>
<td>PM</td>
<td>PM</td>
<td>PM</td>
</tr>
<tr>
<td>PB</td>
<td>PL</td>
<td>PL</td>
<td>PMB</td>
<td>PMB</td>
<td>PMB</td>
<td>PMB</td>
<td>PMB</td>
</tr>
<tr>
<td>PL</td>
<td>PL</td>
<td>PL</td>
<td>PB</td>
<td>PB</td>
<td>PM</td>
<td>PB</td>
<td>PL</td>
</tr>
</tbody>
</table>

TABLE III
RULE BASE FOR ADJUSTMENT OF $Q_c$

<table>
<thead>
<tr>
<th>$\Delta T_{cm}$</th>
<th>NL</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>NZ</th>
<th>PZ</th>
<th>PS</th>
<th>PM</th>
<th>PB</th>
<th>PL</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta Q_c$</td>
<td>PL</td>
<td>PB</td>
<td>PM</td>
<td>PS</td>
<td>PZ</td>
<td>NS</td>
<td>NM</td>
<td>NB</td>
<td>NL</td>
<td></td>
</tr>
</tbody>
</table>

TABLE IV
COMMON BOUNDARY CONDITIONS

<table>
<thead>
<tr>
<th>Item</th>
<th>$T_{in}(^\circ C)$</th>
<th>$d$(mm)</th>
<th>$\Delta T_{in}(^\circ C)$</th>
<th>$\Delta T_{in}(^\circ C)$</th>
<th>$T_{w}(^\circ C)$</th>
<th>$T_{e}(^\circ C)$</th>
<th>$T_{c}(^\circ C)$</th>
<th>$\Delta T_{du}(^\circ C)$</th>
<th>$T_{sw}(^\circ C)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>simulation</td>
<td>800–850</td>
<td>20 ± 1</td>
<td>20 ± 3</td>
<td>0</td>
<td>30 ± 5</td>
<td>30 ± 5</td>
<td>600 ± 5</td>
<td>± 3</td>
<td>± 3</td>
</tr>
<tr>
<td>experiment</td>
<td>800–850</td>
<td>20 ± 1</td>
<td>20 ± 6</td>
<td>± 7</td>
<td>30 ± 5</td>
<td>30 ± 5</td>
<td>600 ± 15</td>
<td>± 10</td>
<td>± 10</td>
</tr>
</tbody>
</table>

Fig. 6. Simulation of searching for the operating point for low-carbon steel (0.23%C) with the transfer coefficient $\alpha$, 90%$\alpha$, and 110%$\alpha$.

Fig. 7. Simulation of searching for the operating point for manganese steel (1.5%Mn) without and with adaptation factor $\eta$.

After obtaining proper operating points, the supervisory system in the higher level closed-loop is switched off from

for the operating points tuning under varying boundary conditions.
TABLE V

<table>
<thead>
<tr>
<th>Item</th>
<th>$d_0$ (mm)</th>
<th>$T_{c0}$ (°C)</th>
<th>$v_0$ (m/s)</th>
<th>$a_0$ (mm/s²)</th>
<th>$\gamma_0$</th>
<th>$N_0$</th>
<th>$Q_{e0}$ (m²/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value scope</td>
<td>20</td>
<td>605</td>
<td>1.8</td>
<td>7</td>
<td>1.91</td>
<td>11</td>
<td>189</td>
</tr>
</tbody>
</table>

control ($T_{cm} = T_{in0} = d = d_0$). The final cooling temperature for most of slabs can be maintained within the range of 600±20 °C.

Compared with the human supervision, the proposed control methodology has obvious advantages that can be summarized as follows:

- shorter time spent on searching for proper operating points;
- higher control accuracy due to the feedforward compensation, and setpoints obtained without algebra interpolation;
- higher economic benefits for the manufacturer due to experiment reduced significantly;
- higher automation level of the laminar cooling process with lower burden of the operator.

V. CONCLUSION

The DCS system has been widely used for the lower level control in the metallurgical industry. Though DCS can maintain a good machine control, however, determining a proper operating point is still a difficult and crucial task to many industrial processes, such as, the laminar cooling process. This paper proposed an SPC-based multivariable fuzzy supervisory control system that could find a proper operating point for the cooling process without accurate mathematical model. The SPC mechanism is designed to simulate the human perception of input signals. Via statistical methods, SPC generate the statistics based control errors for the dominant fuzzy control system. The multivariable fuzzy system, consisting of a group of PI controllers and a parallel decoupling mechanism, is to simulate the decision making function of the human operator. A PI type fuzzy controller is used to search for a proper operating point for each dominant loop through a run-by-run approach. The coupling between the loops will be handled the proper designed decoupling mechanism. An auxiliary compensator is designed to assist fuzzy supervisory system by suppressing the influence from variations of boundary conditions. With the help of the feedforward compensator, the proposed fuzzy system can find the proper operating point automatically in the dynamic environment. The simulation and industrial experiment show the robust performance of the proposed multivariable fuzzy supervisory control system and confirm its viability in the real manufacturing environment. The work presented in this paper not only have remarkable contribution to control of the laminar cooling process, but also shows a good direction for control of batch industrial processes.

REFERENCES


