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Hardware-in-the-loop simulation platform for supervisory control of mineral grinding process

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ABSTRACT

Supervisory control technology is widely used to improve product quality in mineral grinding process (MGP). To ensure safety, new supervisory control method needs to be fully tested before practical application. However, conducting tests in a running process is costly and may put the process equipment in danger, which necessitates extensive simulations to ensure the stability and performance of supervisory controllers. Comparing with the field based test, the numerical simulation is more economic and safer. However, numerical simulations cannot capture all aspects of controlled object, such as sensors, actuators, process, control systems themselves and signal transmissions, which are important to evaluate the control performances. To solve this problem, this paper presents a novel hardware-in-the-loop simulation (HILS) platform for the supervisory control of MGP. By integrating a supervisory control system, a basic loop control system, a virtual actuator and sensor system, and a virtual plant system in to a coherent whole, the HILS platform provides a full-scope simulation environment for the supervisory control. The supervisory control system and the basic loop control system adopt real control systems. The detailed process dynamics are modeled and visualized by the virtual plant system. Further, as an interface between the physical controllers and virtual plant, the virtual actuator and sensor system is used to realize the signal conversion and to simulate the dynamics and faults of the actuators and sensors using data acquisition (DAQ) hardware and configuration software. Effectiveness of platform is demonstrated with a case study, where an intelligent supervisory control method for a typical one stage MGP is tested.

1. Introduction

As a crucial component of the beneficiation process, mineral grinding process (MGP) is used to grind the run-of-mine ore into suitable particle size such that the valuable mineral constituent can be exposed to be recovered in the subsequent classification process [1,2]. In the past, the process control research of the MGP was focused on the basic loop control methods to ensure the process variables follow their setpoints in a stable operation. In order to realize the basic loop control method easily, distributed control systems are widely used.

Long term production practice, however, shows that it is difficult to obtain the desired production only using the basic loop controller. This is because that the inappropriate control loop setpoints will make the MGP work under a non-optimized economic status, thereby leading to high cost and low quality of products. Therefore, a high-performance process control system should ensure that not only process variables can follow their setpoints stably, but also these setpoints are suitable for the optimal process operation. For this reason, a hierarchical approach as shown in Fig. 1 is proposed in [3]. In this framework, a supervisory control system is installed on top of the basic loop control to optimize the control loop setpoints online. The development of a new supervisory control system usually needs to undergo intensive experiments until the control performance meets with the technical requirements.

Experiment in an industrial environment is effective, direct but expensive and often unsafe. Hence, the alternative approach of modeling and simulation is cheap, quick and conclusive. The modeling of mineral process has been discussed for many years [4–7], but the simulation doesn't play a role until personal computers became available in about mid-1980s [8]. The first generation of simulation uses steady state models to offer the best and cheapest way to handle the difficult problems of flowsheet design and optimization. In this period, because of the success of simulation it is also necessary to have a reservoir of professional skills and models, some commercial simulators, such as JKSimMet and USIM Pac, have thus been developed to provide well technical supports [9]. By 1990s, new requirements for high-capacity and high-quality have led mineral processing industry to be concerned with the operation process control and optimization, which requires the modeling of the dynamic relationship between the process variables and the manipulated variables. Hence, a number of researchers began to study the dynamic modeling and simulation [10–14]. Today, there have

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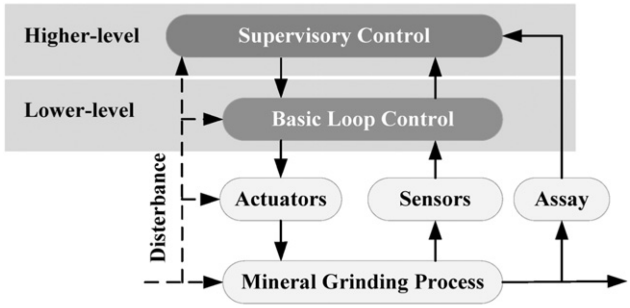


Fig. 1. Hierarchical control strategy for the MGP.

been commercially available dynamic simulators widely used in this field, such as MetSim and SysCAD.

The above simulators have been used to test the software simulated control system. This is the so-called numerical simulation. But the drawbacks of numerical simulation are that they cannot capture the whole grinding system including sensors, actuators, process, control systems themselves and signal transmissions [6,15], and neither do these packages provide a control algorithm programming environment similar to the real control system. This leads to unconvincing results of numerical simulation because programming and testing of the controller are still necessary in practical application.

The gap between the numerical simulation and the actual application had persisted for years until the use of hardware-in-the-loop simulation (HILS) [16–24]. By combining the simulated system with physical hardware, the HILS realizes a full-scope simulation of integrated control system including sensors, actuators, real control units and so forth, which is difficult to achieve solely by the numerical simulator. The HILS has been as an effective verification and validation tool for controller to be applied in many industrial fields. A HILS platform is developed in [16] to verify and validate the safety of nuclear control systems. In [17], a HILS platform consisting of a simulated power system and a real hardware propulsion motor set is proposed to research the performance of electrical ship power system. A HILS platform performed in [18] is used to assess the high-integrity embedded automotive control systems. In recent years, the applications of HILS platform in robotics and automotive systems have been discussed in [19,20] and [21–24], respectively. These applications illustrate the HILS can effectively reduce the risk of accidents at various stages of development: design, implementation, testing, operation, and maintenance stages. For the MGP, the improper loop setpoints will result in the unsatisfying product as well as some faults such as mill overload or underload faults. If the faults cannot be eliminated in time, they will cause damage to devices or even cause suspension of the operation. A HILS platform is thus required for the design and test of the supervisory controller. To our knowledge, however, such platform has not been reported.

Motivated by this issue, this paper focuses on providing a full-scope HILS platform for the design and test of the supervisory control system of the MGP. The proposed platform consists of a supervisory control system, a basic loop control system, a virtual actuator and sensor system, and a virtual plant system. The simulated grinding process (i.e., virtual plant) is linked with the real control systems (i.e., supervisory control system and basic loop control system) through the virtual actuator and sensor system, so that the whole platform can be operated similar to the real system. The major contributions of this work include the following aspects:

- A HILS architecture approaching to industrial grinding system is proposed by integrating actual control system and simulated actuators, sensors and grinding process.
- A virtual actuator and sensor system is developed not only to bridge the simulated grinding process and the actual control system under test, but also to simulate the equipment dynamics and faults.
- A configurable software for supervisory control is developed to assist the design and development of a newly developed supervisory control algorithm for a MGP.
- A flexible modular based simulation environment for the MGP is proposed, where a 3-D visualization component is used to visualize the grinding process vividly.

The paper proceeds as follows. In Section 2, the MGP and its control situation are introduced. The structure, hardware, software and communication protocols of the developed HILS platform are presented in Section 3. An intelligent supervisory control method is designed and tested using the HILS platform in Section 4. Concluding remarks are drawn in the final section.

2. Description of mineral grinding process control

2.1. Process description

The MGP usually consists of a great mill and grader as shown in Fig. 2. The mill is a metal cylinder rotating around its axis at a fixed speed with heavy media inside. Owing to the combined effect of knocking, chipping, and tumbling caused by grinding media, the lump ore is crushed to fine particles. According to the different grinding media, the mill can be categorized based on the grinding media, such as the steel balls and steel rods. The grader is a classification unit used to filter particles grinded from mill and transfer the coarse particles to the mill for regrinding. The overflow slurry with finer particles, as product, is transported to the subsequent procedure. The grader usually employs hydro-cyclone or spiral classifier.

2.2. Control situation

In most grinding process operations, the important production index is product particle size (PPS) (% < 74 μm), which is the key metric indicating the grinding product quality. Due to the fact that undersized and oversized PPS are both unfavorable for the subsequent separation process and those situations may even cause negative economic impact on the whole plant, the control objective is to maintain the PPS within specified range. To realize the above objective, some control loops have to be deployed to ensure the relevant process variables stable, as the PPS is sensitive to some key process variables.

Today, the distributed control systems (DCS) or programmable logic controller (PLC) are deployed in almost all of the control loops in the grinding process. Unfortunately, production practice indicates that the plant still often operates under a non-optimized economic status, thereby producing low quality product in high-energy production. The reason is that “with respect to the economic performance of a MGP plant, the controller performance is most probably not as important as the right selection of the setpoints” [1]. In practice, these loop setpoints are normally regulated by on-site operators. For the operators, however,

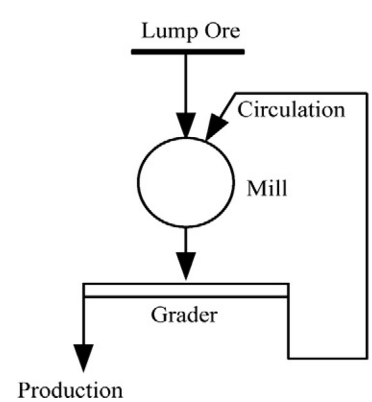


Fig. 2. Flowsheet of grinding process.

it is nearly impossible to adjust loop setpoints timely and accurately in the presence of frequent fluctuations of ore properties (such as ore hardness and particle size).

Consequently, it would be useful to supervise the loop control system with an optimizer that may change the operating setpoints during process operation. Until now, there have been some attempts on solving this supervisory control problem. These begin with some model-based control and optimization methods, such as real-time optimization (RTO) [25], model predictive control (MPC) [2,26–28] and adaptive decoupled control [29,30]. But, these methods are hard to be applied in practical MGPs, as accurate modeling is difficult to achieve or the established models do not accurately describe the actual dynamic processes. Recently, intelligent technologies (i.e., rule based reasoning (RBR) [31], fuzzy logic [32], case based reasoning (CBR) [33], neural network [34], and reinforcement learning [35]) are used or integrated together to realize the supervisory control for the practical MGP.

3. Architecture of HILS platform

Designs of supervisory control based on intelligent technologies rely heavily on the experiments and historical operating data. Different processes need diverse supervisory control structures or algorithms. There is no unified and effective methodology for the supervisory control. In fact, the dynamics of actual plants, to a large extent, differ from each other indeed. This indicates that the experiment-based verification should be adopted to validate and improve the supervisory control system for a new process.

To avoid high-cost and high-risk test of the control system in real industrial plants, a HILS platform consisting of four systems (i.e., a supervisory control system, an embedded PLC-based basic loop control system, a virtual actuator and sensor system, and a virtual plant system) is proposed as shown in Fig. 3. According to the industrial grinding system whose structure is illustrated in Fig. 4, the four components are integrated together via a set of complex communication network to provide a distributed simulation environment similar to the real industrial system.

Different from the numerical simulation that cannot capture all aspects of a grinding process, the HILS supports full-scope simulation, as all the devices and process in actual industrial system are reproduced by similar hardware or simulated by software components. In the HILS platform, the structure and network of the control system under testing are the same with industrial control system. The real plant is represented by the virtual plant, which simulates all the dynamics of grinding

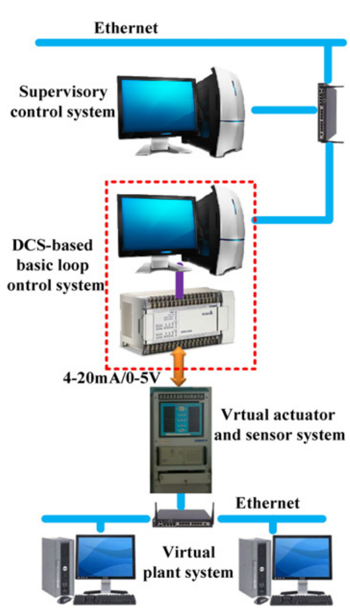


Fig. 3. Structure of HILS platform.

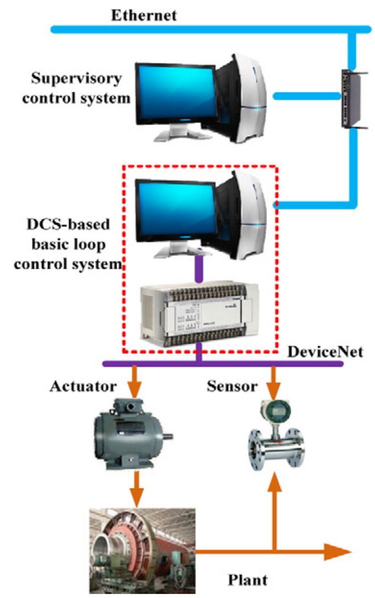


Fig. 4. Structure of industrial system.

operation. The control system is connected to virtual plant by the virtual actuators and sensors system in such ways the verification of control system can be carried out.

For the proposed HILS platform as shown in Fig. 3, the data flow is shown in Fig. 5, which briefly described as follows.

- According to the desired PPS r^*, a set of loop setpoints y^* are generated by the supervisory control system and downloaded to basic loop control system via Ethernet.
- To maintain the process variables y follow their setpoints y^*, the control inputs u are turned rapidly by the loop controller first, and then transferred to the virtual actuator and sensor system via electric cables.
- Through the signal conversion and actuator simulation in the virtual actuator and sensor system, the control inputs u are converted to $\tilde{u}$ that will be transferred to virtual plant via Ethernet.

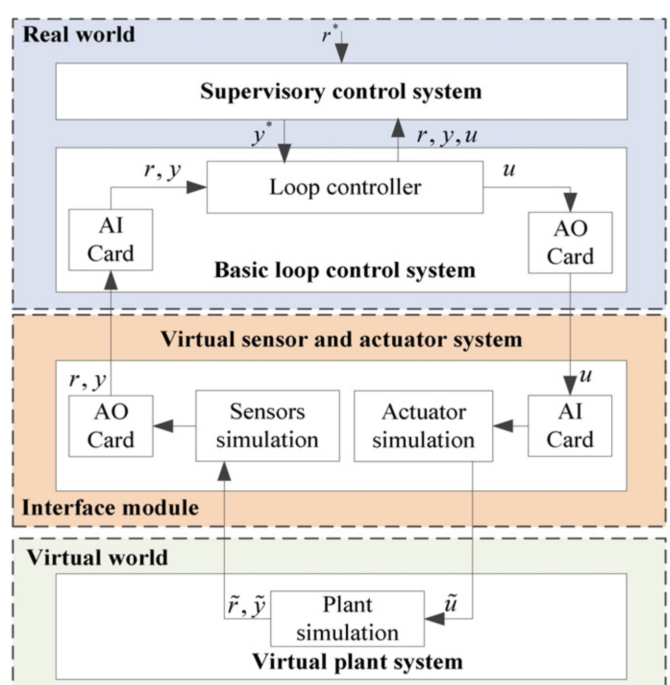


Fig. 5. Information flow of HILS platform.

Table 1
Main notation.

Name	Description
r^*	Desired product particle size
r	Actual product particle size
$\tilde{r}$	Simulated product particle size
y^*	Control loop setpoint
y	Actual control loop output
$\tilde{y}$	Simulated control loop output
u	Actual control loop input
$\tilde{u}$	Simulated control loop input

- In the control of $\tilde{u}$, the virtual plant system generates the control loop outputs $\tilde{y}$ and the PPS $\tilde{r}$ first, and then feeds them back to the virtual actuator and sensor system via Ethernet.
- Consider that each feedback signal needs to be detected by a sensor, $\tilde{y}$ and $\tilde{r}$ will undergo sensor simulation and signal conversion in succession in virtual actuator and sensor system.
- The signals y and r are collected by the basic loop control system to update u. Meanwhile, these signals are transferred to the supervisory control system.
- When the supervisory control system receives the feedback signals, it will recalculate the loop setpoints y^*, and send them to the basic loop control system. Such that, a closed-loop control cycle is completed.

Table 1 lists the notations used in the Fig. 5.

4. Implementation of HILS platform

4.1. Virtual plant system

Dynamic simulation is crucial for the design and testing of a control system. To reconstruct the grinding operation process in HILS platform, a 3-D simulation software for virtual plant is developed and resides on a computer. The software provides three components i.e., modeling component, 3-D visualization component and communication component. The modeling component is employed to establish the simulation models of the grinding process; the 3-D visualization component is used to construct the process operation to screen; and the data exchange between the above two components is achieved by the communication component. The functional units used in each component as well as their relation are shown in Fig. 6. A brief description is given here, but for more details refer to our early work [36,37].

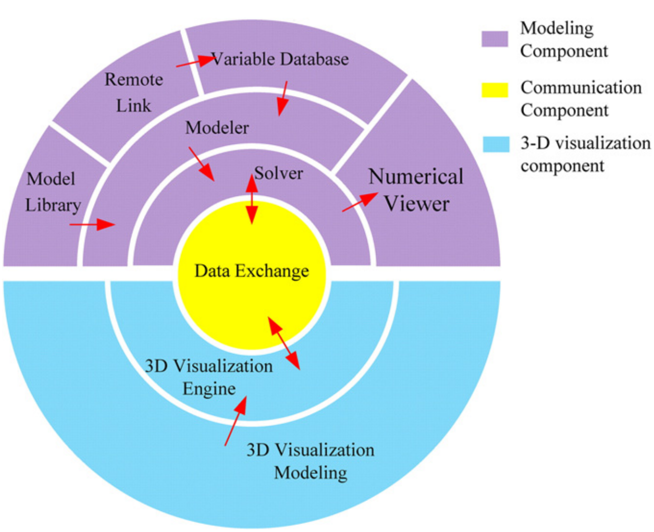


Fig. 6. Structure diagram of 3-D simulation software.

4.1.1. Modeling component

Since MGP involves very complex phenomena, it is common to divide a whole MGP into several units, where each unit represents an operation subprocess. Different modeling technologies can be used according to the subprocess features. Finally the whole MGP can be assembled by connecting these unit units. The above modeling approach makes the modeling easier for users to configure a simulation scenario, since the addition and deletion of units do not necessarily change the simulation strategy. In addition, material flow can be easily seen from the unit's relationship.

For the above reason, the modeling component adopts a modular-based building approach. Each unit model can be developed in terms of customized block written in computer code first, and then encapsulated in a unit module by using a *Modeler*. The encapsulated models are stored in a *Model Library*. Further, the *Modeler* provides a drag-and-drop type of interface for definition of connectivity of the unit models. The variables involved in the connectivity definition are divided into two kinds, namely local variables and remote variables. The local variables that are only used in model solving, whiles the remote variables are employed for not only model solving but also remote data communication with the virtual actuator and sensor system. All of these variables are created by a *Variable Library*. After the model is established, the model simulation is performed using a *Solver*, which provides basic numeric routines. During the simulation process, the *Solver* will update the model variables to a *Numeral Viewer*, which contains various pop-up windows where users can change the settings of the models and view the simulation results by means of tables and trends. In this way, the simulations of diverse plants with different model parameters can be carried out.

For convenience, the models of typical operation units (such as mills, spiral classifier, hydro-cyclone) have been encapsulated in the *Model Library*.

Traditionally, the grinding process are modeled with either mechanism technique or data-driven technique. But, these two kinds of techniques have obvious inherent advantages and disadvantages. If used alone unsatisfactory results are often obtained [3]. Therefore, we adopts a hybrid modeling technique which could obtain better and more reliable performance by integrating the above two kinds of techniques. Specifically, each grinding operation unit is modeled with mechanism technique first, and then the data-driven technique is adopted to estimate the model parameters based on the real-time data. In this way, it is not only partly compensate the unmodeled dynamics but also make models adjust adaptively according to diverse operation conditions, thereby having the simulation cover the entire real process.

For the mill, its mechanism modeling methods can be traced back to 1840s, and extensive research work was carried out so far. According to different modeling principle, the mill can be described by different mathematical models, such as energy consumption model [38], matrix model [39], kinetics model [40] and population balance model [41]. Since the energy consumption model and matrix model belong to static models, and kinetics model refers only to batch grinding process, they cannot be used to simulate the continuous grinding dynamics. The most widely applied dynamic simulation model is the population balance model, which is used with the energy-specific or empirical selection function. But, population balance model is usually not in full agreement with the real process in its entire operating range because of the overlooked variation of the selection function in different operation conditions. To improve the simulation performance, on the basis of the population balance model, a TSK (Takagi–Sugeno–Kang) neuron-fuzzy network is adopted to estimate the model parameters using the comprehensive data collected in plants over a long period covering a wide range of ore types and operating conditions. Those details can be referred in [37].

For the hydrocyclone, its dynamics can be neglected as the response of equipment is virtually instantaneous [7]. Currently, most hydrocyclone models are based on the equilibrium orbit theory, the residence time theory or the turbulent two-phase flow theory. In this system, the model of hydrocyclone is derived from the empirical model of Lynch and Rao [42], which includes some mass balance equations, a classification efficiency function, a corrected cut-size function and a sharpness of classification function. The model parameters are determined through a Radial Basis Function Neural Network (RBFNN) which is trained with the actual data collected from the plant [37].

For the spiral classifier, its model is similar to the hydrocyclone model [43]. But the classification efficiency function becomes more complex because of mixture effects [44]. Besides, a time delay is added in its recycle output because the particles sinking to the bottom need time to be transported to the upper end of the spiral classifier by metal spiral slices. Similar to the hydrocyclone model, its model parameters are also evaluated by using RBFNN.

4.1.2. 3-D visualization component

The modeling component can make it easy for users to graphically develop the flowsheet models of complex processes. But when it is used to train new operators, it may be ineffective, since the flowsheet model cannot visually and directly display the operation condition of the equipment. Consequently, the 3-D visualization component is developed.

In this component, the 3-D visualization models for operation unites are created first using the commercial package MultiGen Creator. And then a VTree-based visualization engine is employed to fulfill the visual simulation of plant. Furthermore, the engine provides an interface for the communication component to read and write its data from and to the modeling component.

4.1.3. Communication component

This component is a data transmission channel between the modeling component and 3-D visualization component. Since OPC (Ole for Process Control) [45] can facilitate integration and communication among heterogeneous networks, it has been served as an interoperability standard for the industry control. In our platform, an OPC server is developed and available for both the modeling component and 3-D visualization component with individual OPC client. Such that, when the data in any OPC client change, OPC server will immediately detect it and update the data on the server correspondingly. Then, the OPC server will send the updated data to the other OPC clients. In this way, the data exchange is performed effectively.

4.2. Supervisory control system

The virtual plant system lays a significant foundation for control system design and testing. Currently, the commercial off-the-shelf (COTS) control software packages (i.e., Aspen Plus Optimizer, Profit Optimizer, DMCplus, DeltaV Predict/Pro, etc.) are referred to model-based methods (i.e., RTO, MPC, etc.). But in mineral industry, the actual processes are always difficult to be modeled mathematically. Hence, the above COTS packages are difficult to be applied. To solve the problem of the setpoints optimization, it is necessary to adopt data-driven or intelligent control methods. Due to the fact that the idea of data-driven or intelligent controller design is to formulate the controller strategy and then specify each part of the controller [3], the easiest way for controller development is to develop algorithm unit individually first and then to connect them according to the control strategy, thereby building a whole controller. Hence, a modular-based configuration software is in urgent need. To our best knowledge, however, such software has not been reported so far.

Motivated by this, a configurable software is developed. This paper only focuses on the framework of the software and gives a brief description of the main modules. The technologies used in the modules, however, will not be elaborated too much here for limit of space. The Fig. 7 shows the main modules developed in this software and their relation.

Supervisory controller is essentially a logical assembly of different algorithm units, the abundance, availability and extendibility of the algorithm units are thus key for the system usability. For this reason, an *Algorithm Library* is developed to provide a number of basic algorithms units for controller configuration. In the *Algorithm Library*, the basic units are classified and saved in different toolboxes: a) sources toolbox providing several signals such as sine signal; b) I/O toolbox providing input/output function blocks (FBs); c) basic math toolbox providing canonical mathematical operation FBs such as add, subtract, multiply and divide; d) control toolbox providing some data processing algorithms for control.

In the control toolbox, several standard control algorithms, such as PID, fuzzy logical, MPC, have been developed as basic units. This greatly make the building of controller easier. But when it is coming to a novel controller made up of non-standard complex algorithms, such as case or rule based reasoning, it still be a hard work as it is difficult if not impossible to realize those complex algorithms by reusing the basic units.

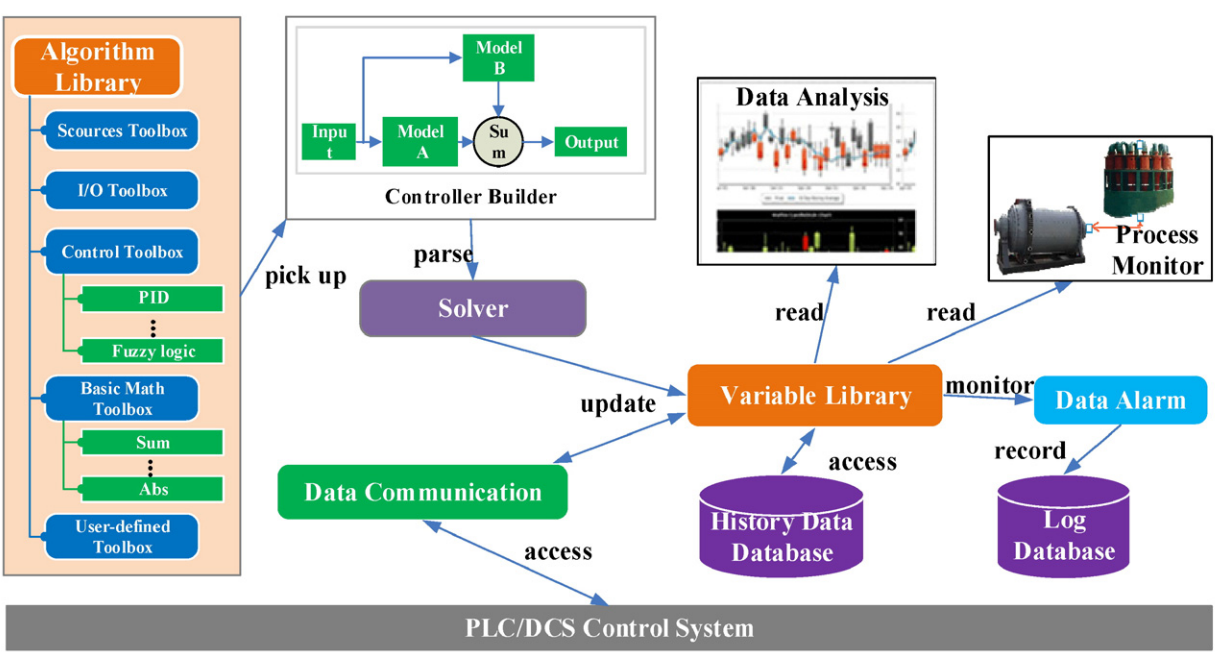


Fig. 7. Structure of the configurable software of supervisory control.

Therefore, the system provides a user-defined toolbox for extending the functionality of the algorithm units by adding routines. The routines can be developed directly using MATLAB platform according to algorithms, or encapsulated as dynamic link library (DLL) files using C++. To achieve the purpose of the reuse of algorithm resources, the user-defined algorithm units are allowed to be embedded in *Algorithm Library*.

When starting up the controller, the *Controller Builder* will call a *Computational Engine* to execute the FBs one by one according to data flow, meanwhile the *Variables Library* will update the data for *Process Monitor*, *Data Analysis* and *Data Alarm*. *Process Monitor* can monitor the process operation situations in the supervisory control system. The *Data Analysis* provides control performance statistics and data visualization for user to judge the effectiveness of the supervisory control algorithms. *Data Alarm* is used to detect the abnormal variables whose values exceed the normal operating range, and also give users a piece of warning message to do corresponding responses. With regard to abnormal variable, it is usually caused by either control algorithms or sensors faults. This is because that improper control algorithms maybe generate a set of incorrect loop setpoints out of the normal operating ranges. In the condition of sensor faults such as interruption and short-circuit, the measured data will always become zero or less than zero, as output of sensor will be less than the minimum of industrial standard signal (standard range is often 4 ~ 20 mA or 1–5 V). Therefore, the *Data Alarm*, to a certain extent, can diagnosis some faults in control algorithms or sensors by detecting the abnormal variables, thereby warning the operators to switch the controller or manually set the loop setpoints to keep the grinding process operation safe and successive. The warning message will be recorded into a *Log Database* for analysis.

4.3. Basic loop control system

The aim of the basic loop controller is to force the control loop outputs to track their setpoints downloaded from the supervisory control system, while maintaining safe process operations. Any control platform supporting OPC protocol could be used in this platform. Industrial PLC is the best as it could make the HILS platform more close to the actual system. But, the use of industrial PLC will make cost significantly increase. Compared with the industrial PLC, embedded soft PLC (ES-PLC) has the advent-ages of smaller size, faster computation speed, and lower price. Therefore, an ES-PLC-based basic loop controller is employed to make the platform more economical and convenient to use.

The ES-PLC is composed of two parts i.e. programming system and running system, which reside in a personal computer (PC) platform and an embedded hardware platform, respectively. The programming system is used to develop the controller with the programming language specified by IEC 61131 standard, to check syntax, to generate object code, to download the object code to the running system, and so on. The running system is responsible for parsing the executing the object code, collecting data and sending control commands via IO interface. Its overall architecture is shown in Fig. 8.

The programming system adopts a development package, namely MULTIPROG 5.35 Express developed by KW Software GmbH. It provides a fully graphic editor with auto routing, a text editor with syntax highlighting and a variables grid editor. Further, it supports users in efficient programming in each IEC 61131 language. In addition, it adopts an open compiler technology namely common intermediate language (CIL), in this way the user can program in IEC 61131 or execute complex calculations and object-oriented C++ programming in Microsoft Visual Studio. The entire program can be translated to object code and then be executed at high performance in the existing embedded systems such as ARM, ×86, PowerPC, SH or Cortex [46].

The running system is an embedded system that is developed using an ARM9 microprocessor (AT91SAM 9263). Its peripherals include flash memory unit, power circuit, boot startup circuit, I/O circuit, isolation conditioning circuit, and communication peripherals such as internet access, serial port and USB port. Further, an industrial standard communication protocol, namely Modbus, is supported. It is worth noting that the communication protocol between the supervisory control system and the basic loop control system is OPC that is different with Modbus. Therefore, protocol transformation is necessary in this platform. To solve this problem, a communication management software package namely KEPSeverEX developed by Kepware Technologies Inc. is adopted. This software package supports an array of open standards. Through Modbus protocol, it can create and update OPC items according to the tags used in the running system. Meanwhile, supervisory control system can read or write OPC items synchronously or asynchronously via OPC client. Such that, the communication between the supervisory control system and basic loop control system is achieved steadily and safely.

4.4. Virtual actuator and sensor system

Although the Ethernet used in the virtual plant system enables multiple virtual plant systems to perform simultaneously, it is totally different from the industrial standard. The issue of communication between Ethernet signal and standard industrial signal (4–20 mA and 1–5 V) is thus raised. To enable interfacing between these different signals, an interface module namely the virtual actuator and sensor system (see Fig. 9) is developed using an industrial control computer (IPC) with an Ethernet network card, several signal conditioning cards and data acquisition (DAQ) cards manufactured by Advantech Co., Ltd.

Using the signal conditioning cards (such as PCLD-880), the industrial signals are converted to standard signals available for the DAQ (such as PCL-1712L and 1727U card, suitable alternatives are those by Agilent and Omega, or custom micro-controller boards) cards first. After that the DAQ cards will acquire these standard signals through 20-pin flat cables. Following acquisition, the signals need to be processed in IPC

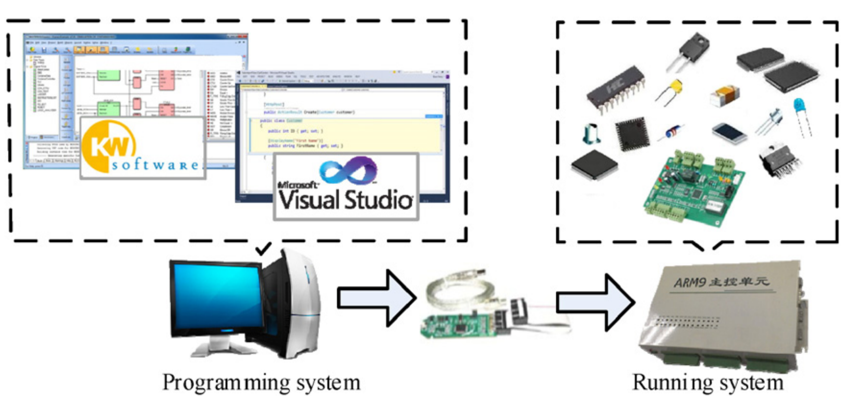


Fig. 8. Structure of the ES-PLC-based basic loop controller.

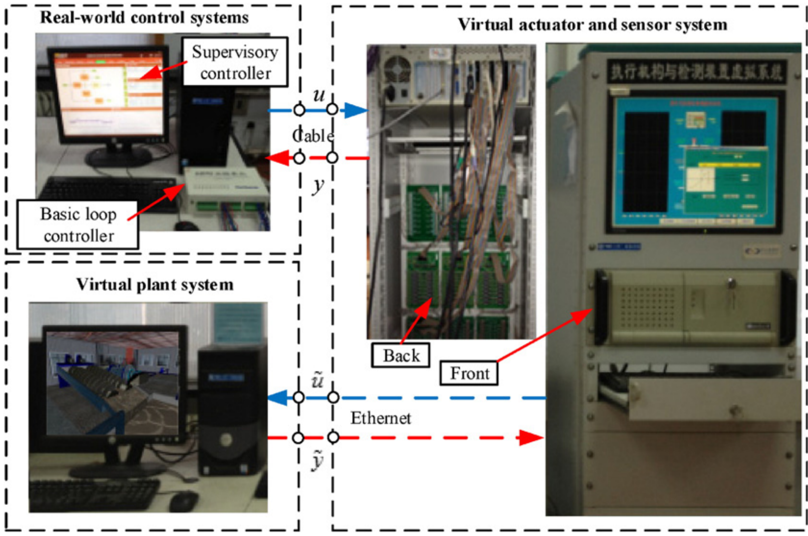


Fig. 9. Implementation of communication of HILS platform.

and then sent to the Ethernet card for output. An alternative way is that Ethernet signal is collected by IPC and then sent to DAQ cards for output after essential signal processing.

In the signal processing procedure, due to the totally different of scales of standard industrial and Ethernet signals, the signal conversion is required. To make the experiment platform more practical, inherent characteristics of the actuators and sensors (such as dead zone, saturation, time-lag, zero drift and so forth) have to be considered. Furthermore, owing to the fact that the actuators and sensors are often not working properly in practice because of maintenances or faults like sensor interruption, short-circuit, and valve stuck, it is also necessary to consider the normal and abnormal conditions, which enables the user can conduct fault diagnosis and fault tolerant control experiments in this platform. Furthermore, different control strategies can be tested in the condition of different sensors operating healthily. For instance, if fresh ore feed rate and adding water flow can be measured normally it is common to employ feedforward control strategy to control slurry density, if not the feedback control strategy based on the measured slurry density is always adopted. To keep the process operation safe and successive in any condition, the above two control strategies are both required. Using the virtual actuator and sensor system, the users can choose the available measured signals by setting the condition of sensor, and then test the corresponding control strategy.

To realize the above requirements, a HMI configuration software, namely Rsview32 developed by Rockwell Automation, Inc., is utilized. Using the build-in VBA programming environment, the signal processing procedure is developed. For the user interface employed for adjusting data processing parameter, it is conducted by using the build-in graphical editor. Due to limited space, no more details here.

In the following section, the validation of platform is performed by a case study about an intelligent supervisory control for a typical MGP.

5. Validation of HILS platform

5.1. Typical MGP

A typical MGP, mainly consists of a feed conveyor, a ball mill and a spiral classifier, is graphically shown in Fig. 10. The raw material of

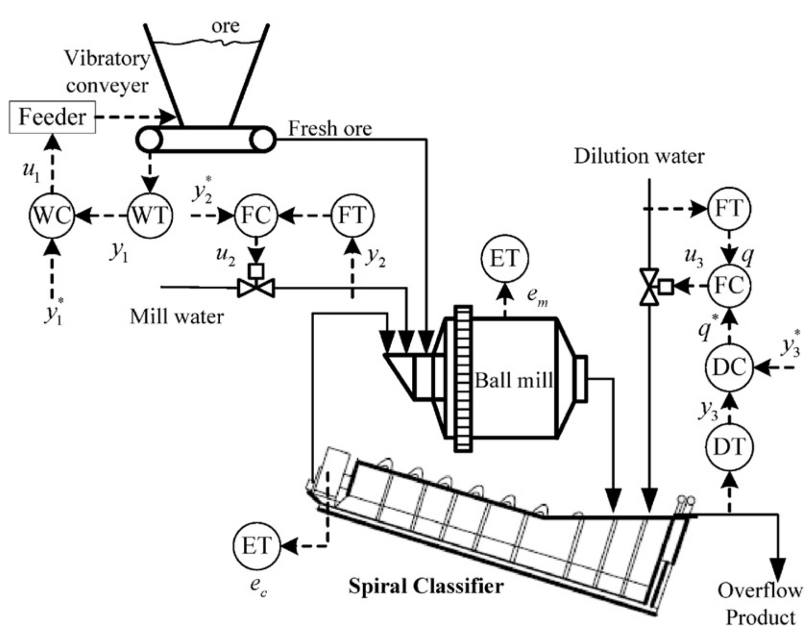


Fig. 10. Flow chart of mineral grinding process.

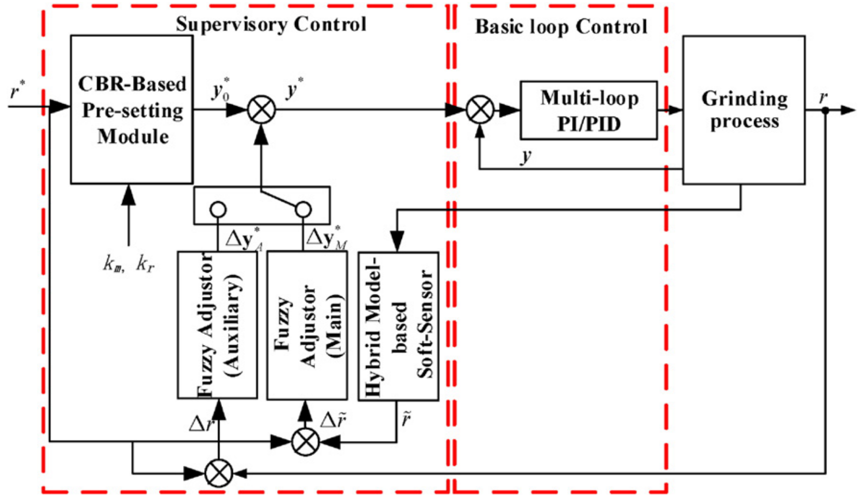


Fig. 11. Structure of optimal control scheme.

this MGP is the undressed ore generated from the crushing procedure, and the final production is the overflow slurry of spiral classifier. PPS is thus the particle size of the overflow slurry.

During the operation, the coarse fresh ore is first fed continuously into the ball mill by the conveyor at a certain speed, together with a certain amount of inlet mill water. Then, the ball mill is responsible for grinding the coarse ore to finer sizes. In this grinding process, mill load and slurry density determine the grinding efficiency, besides the mill structural parameters such as steel balls and rotation speed. For those two influencing factors, too high and too low both attenuate the grinding efficiency. When the mixed ore slurry including both coarser and finer particles is continuously discharged from the mill into the spiral classifier, gravity classification operation begins. Due to the fact that difference of particles' sedimentation rates is the reason for particle classification, and the sedimentation rates is essentially influenced by the slurry density, the classification performance is thus dependent on the classifier slurry density.

From the above analysis, it can be seen that since the structural parameters of mill the classifier can be considered as constant within a certain operating time, the mill load, mill slurry density and classifier slurry density are key factors for the MGP operation. But the mill load and mill slurry density are unmeasurable in practice. Fortunately, they, to a certain extent, can be adjusted by the fresh ore feed rate and water flow rate of the ball mill, respectively. As a consequence, the fresh ore feed rate, water flow rate of the ball mill and slurry density of the spiral classifier are selected as the operational variables $y_i(i = 1,2,3)$. To maintain $y_i(i = 1,2,3)$ around its setpoint $y^*{}_i(i = 1,2,3)$, three control loops are deployed as shown in Fig. 10, where –C and –T express controller and instrument, respectively, and W–, F–, D– and E– stand for weighing, flow rate, density and current, respectively.

Since the speed of the ore feed belt is constant, the feeder motor is unique device to regulate y_1. Therefore, frequency of feeder motor u_1 (Hz) is selected as manipulated variable of the control loop for y_1. It is well known that water flow is controlled by valve position when water pressure is constant, the valve position u_2 (%) of mill water is thus selected as manipulated variable of the control loop for y_2. For y_3, the manipulated variable is dilution water addition rate q (m^3/h), but q is controlled by valve position of dilution water u_3 (%). As a result, a cascade control loop is adopted as shown in Fig. 10.

5.2. Design and development of controller

5.2.1. Design of intelligent supervisory control

Since the controlled object of the supervisory control is a generalized object that includes not only the grinding process but also the basic loop control system, the dynamic behavior of the basic loop control system will in turn influence the performance of the supervisory control. Therefore, a satisfying basic loop control system is necessary for the accurate evaluation of the supervisory control. In contrast with the modeling operation process, it may be easier to model the loop processes. Therefore, the traditional control methods like PID and the advanced control methods like MPC both can be adopted. But, it is worth noting that the performance of those control methods highly depends on the accuracy of system modeling and parameter identification. Thus, for the multiple-input-multiple-output (MIMO) systems with strong couplings like the MGP, it is better to model for different channels by means of various models according to process characteristics, such as linear transfer function models and nonlinear models.

In this paper, increment PID controllers are developed using the ES-PLC. To accurately assign the controller parameters, three loop processes mentioned in Subsection 5.1 are modeled first in terms of linear transfer functions, and then parameter adjustments based on Refined Ziegler-Nichols (R-ZN) are employed using the established models. The later experiments show that the increment PID controllers can meet with the technical requirements, such as steady-state error, overshot, rise time and so forth.

For the supervisory control system, it is clear that model-based methods require an accurate mathematical model, which makes them not suitable for the industrial grinding plant. In our early work [31,32], some intelligent techniques are employed to achieve the supervisory control of the MGP. In this work, to evaluate and validate the HILS platform, an intelligent controller to maintain the PPS within the desired range ($r^*-0.2\%$, $r^* + 0.2\%$) is developed and tested in this platform. The controller consists of a case based reasoning (CBR)-based pre-setting module, a PPS soft-sensor, and two fuzzy adjustors (main and auxiliary adjustors). Its structure is shown in Fig. 11. Each part is briefly reviewed as follows (for details see [31,47]).

1. CBR-based loop pre-setting module

This module is referred to as a steady optimal controller that provides a set of proper pre-setpoints $\boldsymbol{y}_0^*$ ($y_{1,0}^*$, $y_{2,0}^*$ and $y_{3,0}^*$) according to the desired PPS r^*, boundary condition (fresh ore hardness k_m and size

Table 2
Case structure.

Time	Case description							Case solution		
	c_1	c_2	c_3	c_4	c_5	c_6	c_7	s_1	s_2	s_3
t	y_1	y_2	y_3	k_m	k_r	r^*	r	$y_{1,0}^*$	$y_{2,0}^*$	$y_{3,0}^*$

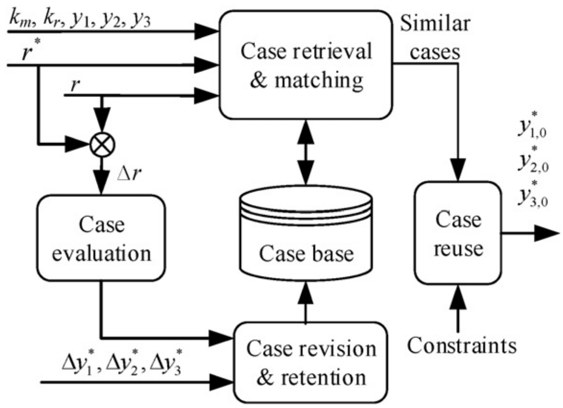


Fig. 12. Reasoning flow of the CBR-based loop pre-setting module.

distribution k_r), and the current operating condition (y_1, y_2, y_3 and r). Based on the historical data, the optimum loop setpoints responding to the different conditions are extracted to a case. The structure of the case is shown in Table 2. t stands for the time of case created and stored; c_i, $i = 1,2,\ldots 7$ denote case description features; s_i, $i = 1,2,3$ are the case solutions expressing the optimum loop setpoints. In such case, k_m and k_r are of enumerative style. Five ordered figures {1,1.5,2,2.5,3} are employed to demarcate the linguistic variables {bad, relatively bad, medium, relatively good, good} for k_m and {large, relatively large, medium, relatively small, small} for k_r. In the testing stage, the experiments will be carried out in the case of variations of k_m and k_r.

Fig. 12 presents the reasoning flow of CBR-based loop pre-setting module. It includes case retrieval and matching, case reuse, case evaluation, and case revision and retention (for details see [31]). The case retrieval and matching is used to find the matching cases, which are similar with the current situation. Applying these matching cases, the case reuse will generate the current solution. If the case evaluation detects r exceeds its desired range, it will switch on fuzzy adjustors to compute the adjusting increments $\Delta \boldsymbol{y}^*$. After that the case revision and retention will revise the case solution to $\Delta \boldsymbol{y}^* + \boldsymbol{y}^*_0$, and store this revised case.

2. PPS soft-sensor

In many real plants, since online measurement devices are of high cost and failure rate, the measurement of PPS always relies heavily on offline laboratory assay. But the assay is a time-consuming process in fact. The soft-sensor technique is thus required to estimate the PPS online if one wants to obtain the satisfying product throughout.

Soft-sensor focuses on the process of estimation of some system variable or product quality by using mathematical models and data acquired from some other available physical sensors. This paper adopts a hybrid PPS soft-sensor that is composed of a mechanistic model and a data-driven model to achieve the nonlinear mapping in Eq. (1).

$$\tilde{r}(k) = \phi_S(y_1(k), y_2(k), y_3(k), e_m(k), e_c(k), \tilde{r}(k\text{-}1), k_m, k_r) \tag{1}$$

The mechanistic model employs PBM to catch the main dynamics, and data-driven model uses a random vector functional link network (RVFLN) with improved robustness to compensate the unmodelled dynamics. The details can be found in [47]. The PPS soft-sensor is the foundations of fuzzy adjustors described as follows.

3. Fuzzy adjustors

During the grinding operation, the equipment parameters (e.g., grinding media and dimensions of metal spirals, etc) always vary with time. This will make the setpoints drift away from the optimum, thereby leading to control error of PPS. Hence, two fuzzy adjustors (one is main adjustor, the other is auxiliary adjustor) are used to compensate the effects of disturbances caused by these time-varying parameters through adjusting the setpoints online. Once the PPS is found to exceed the desirable range, the adjustors will be activated to realize the following multivariable nonlinear mappings respectively

$$\begin{cases} \Delta \boldsymbol{y}^*_M = \phi_M(\Delta\tilde{r}, u_1, u_2, u_3, k_m, k_r) \\ \Delta \boldsymbol{y}^*_A = \phi_A(\Delta \mathrm{r}, u_1, u_2, u_3, k_m, k_r) \end{cases} \tag{2}$$

where $\Delta \boldsymbol{y}^*_M = [\Delta y_{1,M}^*, \Delta y_{2,M}^*, \Delta y_{3,M}^*]^T$; and $\Delta \boldsymbol{y}^*_A = [\Delta y^*_{1,A}, \Delta y^*_{2,A}, \Delta y^*_{3,A}]^T$; $\Delta\tilde{r} = r^* - \tilde{r}$ is the deviation between the desired PPS and estimated PPS; $\Delta \mathrm{r} = r^* - r$ is the deviation between the desired PPS and assaying PPS.

The arithmetic of the auxiliary adjustor is similar to the main adjustor. Due to limited space, only the main adjustor is briefly viewed here, but for more detailed information please refer to the literature [31]. The main adjustor, whose structure is illuminated in Fig. 13, includes a fuzzy inference module, a coordination module and an adaptive module. In the main adjustor, the fuzzy inference module integrates four traditional fuzzy logic inference mechanisms (i.e., F_{of}, F_{dm}, and F_{dc}) to compute the scale factor b_{M1}–b_{M6} for the adjusted increments $\Delta \boldsymbol{y}^*_M$. Consider that the grinding operation is sensitive to ore properties, the following adaptive module is adopted based on the two adaptive factors k_m and k_r.

$$\Delta \boldsymbol{y}^*_M = \begin{bmatrix} \Delta y^*_{1,M} \\ \Delta y^*_{2,M} \\ \Delta y^*_{3,M} \end{bmatrix} = \begin{bmatrix} b_{M_1} & b_{M_2} & 0 \\ b_{M_3} & b_{M_4} & 0 \\ 0 & 0 & b_{M_5} \end{bmatrix} \begin{bmatrix} k_m \\ k_r \\ 1 \end{bmatrix} \tag{3}$$

To enhance the production rate with a satisfactory PPS, the coordination module is used to coordinate each fuzzy logic inference mechanism using the following scheme.

- If the PPS is fine, to enhance the mill throughput, start the inference F_{of} to increase y_1, while set b_{m3}–b_{m5} as zero to keep the former value of y_2 and y_3.
- If the PPS is coarse, to keep the mill throughput, it should start F_{dm} and F_{dc} to adjust y_2 and y_3 respectively, whereas set b_{m1} and b_{m2} as zero to keep the former value of y_1.
- If the PPS is too coarse, the four inference mechanisms will be started to reduce y_1 and adjust y_2 as well as y_3 accordingly.

5.2.2. Controller development

Using the user-defined toolbox of supervisory control software for Matlab, each algorithm mentioned above has been developed. The

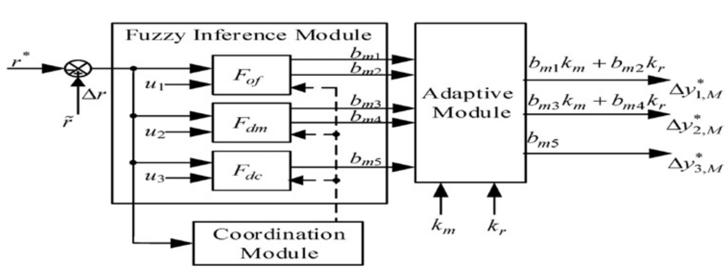
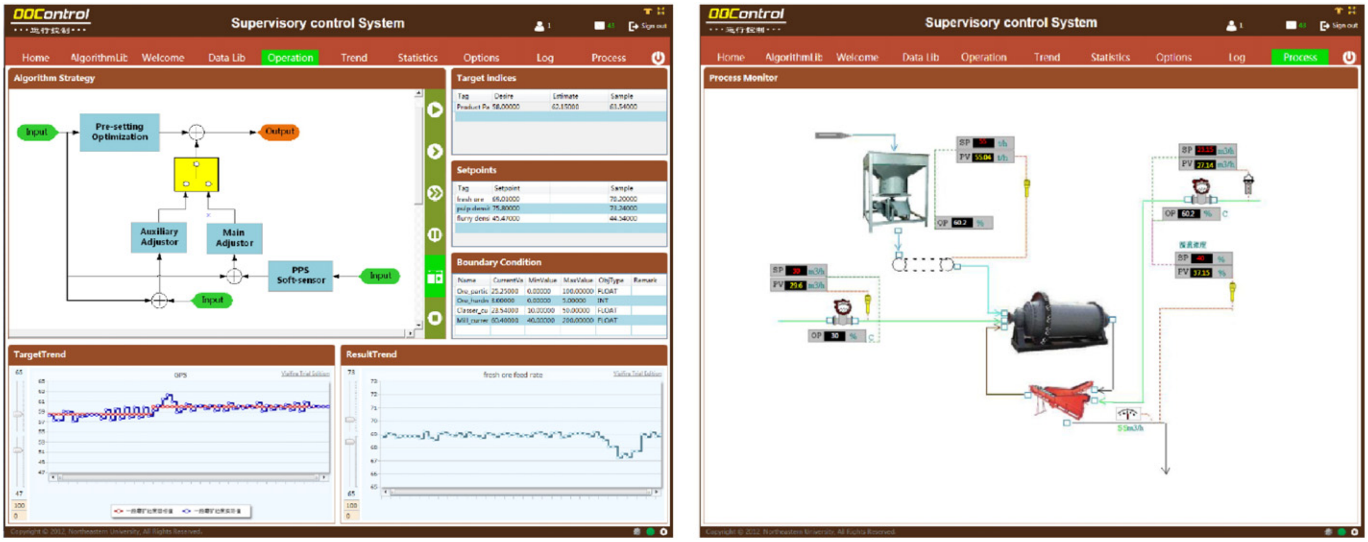


Fig. 13. Structure of fuzzy main adjustor.



(a) (b)

Fig. 14. Snapshot of supervisory control software: (a) Operation interface; (b) Process monitor interface.

data used in CBR-based loop pre-setting algorithm is realized using Microsoft Access 2010. Then, we drag and drop the developed algorithm module form algorithm library one by one. A snapshot of main operation interface is shown in Fig. 14(a). The controller configuration interface is shown on the top left corner, and some data tables and trends are displayed on the bottom side and the top right corner respectively to support the decision making of researchers. The snapshot of process monitor interface is shown in Fig. 14(b).

To test the developed controller, the models of ball mill, spiral classifier, vibratory conveyer and valves need to simulate the whole grinding process besides the relevant actuator and sensor models that built in virtual actuator and sensor system. Using the virtual plant software, the simulation models are established and shown in Fig. 15(a). The project information, model property, and model library are shown on the left, bottom, and right side respectively. Furthermore, the virtual reality of grinding process is built as shown in Fig. 15(b). This part is not necessary for the testing of the controller, but it is useful for gaining some insight into the grinding process vividly.

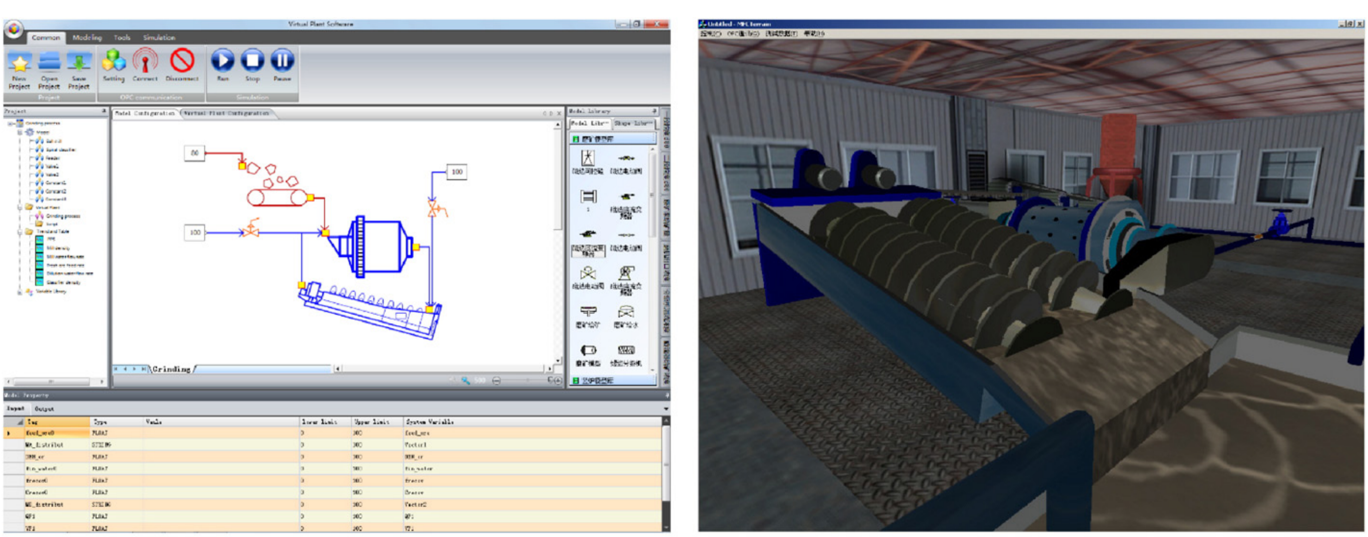
5.3. Testing of controller

In practice, the adjustment of the supervisory controller is unavoidable. So the supervisory control software must be reconfigurable. In this subsection, this feature will be confirmed by modifying the controller.

Firstly, the PPS soft sensor and the main fuzzy adjustor are removed from the controller. The supervisory control period is set to the same with that of the PPS assay. In the virtual plant system, the following model is established to simulate the assaying process.

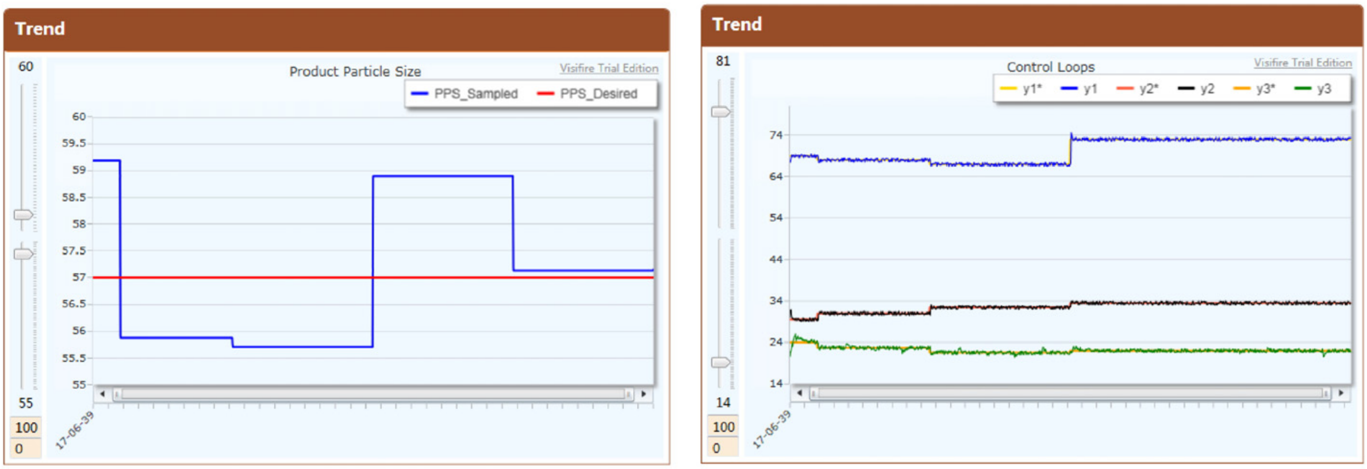
$$r(T) = T_2 \sum_{k=1}^{T_1/T_2} r(T - T_1 + kT_2) \Big/ T_1 \tag{4}$$

where T_1 is the assaying period, and T_2 is basic feedback control period. Eq. (4) indicates that the actual PPS is the statistical value for recent time. In this study, $T_1 = 250$ s and $T_2 = 1$ s.



(a) (b)

Fig. 15. Snapshot of virtual plant system: (a) modeling component; (b) 3-D visualization component.



(a) (b)

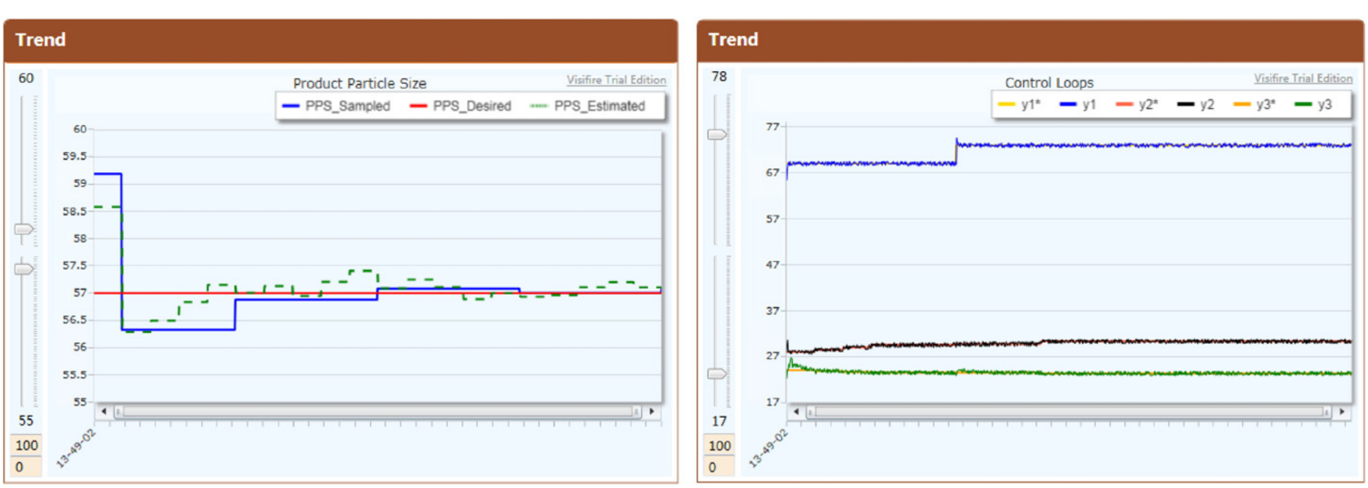
Fig. 16. Control trends without PPS soft sensor and main fuzzy adjustor: (a) PPS; (b) control loop setpoints and outputs.

The control trends without PPS soft sensor and main fuzzy adjustor are shown in Fig. 16. At the beginning of the system operation, the initial pre-setting values for the loop setpoints are obtained, and when assaying PPS is coming, the compensation value for the loop setpoints is generated. The Fig. 16 illustrates that the supervisory control system can (1) collect the process data and assaying PPS from HILS platform, (2) adjust the loop setpoints according to the updated assaying PPS, desired PPS, control loop outputs, and (3) download the adjusted loop setpoints to the basic feedback controller. Furthermore, the basic loop control system can force the control loop outputs to follow the adjusted setpoints timely using the increment PID method. Furthermore, from Fig. 16, it can be observed that the virtual actuator and sensor system as well as virtual plant system can effectively simulate the whole grinding process and feed the accurate process behaviors back to the basic feedback control and supervisory control systems.

From the results, one can see that the current supervisory controller has poor performance. The reason is that the control period T_1 is too large. This cause serious control delay. When the ore property changes, the PPS will fluctuate accordingly. Unfortunately, this controller cannot perceive the fluctuation and adjust setpoints until the next assaying value arrives. It is thus difficult to maintain the PPS within its desired range. This simulation result is consistent with reality, which confirms the effectiveness of the platform.

If the PPS soft sensor and main fuzzy adjustor are added to the supervisory controller, the control performance should be greatly improved. This experiment is carried out in the HILS platform, and the corresponding experiment result can be found in Fig. 17. From Fig. 17, it can be seen that the controller provides accurate online estimate of PP. Based on this estimated PPS, the change of actual PPS can be evaluated in real time online. Whenever the estimated PPS is outside its desired range, the supervisory control system will adjust the loop setpoints according to the error between estimated and desired PPSs. In this case, the control period is set as the period of PPS soft-sensor, namely 50s. In this way, the continued control behavior can be realized during the process operation, and the fluctuation of PPS can be suppressed ahead of the arrival of assaying PPS. As a result, the actual PPS can be maintained within its desired range, which demonstrates almost all of the production are qualified pulp. The result is also consistent with reality.

To further validate the efficacy of the HILS platform, an experiment that enhances the desired PPS by 1% during the grinding operation is carried out. In practice, the desired PPS is obtained from a planning and scheduling system, and it usually varies over time. Hence, this



(a) (b)

Fig. 17. Control trends with the PPS soft sensor and main fuzzy adjustor: (a) PPS; (b) control loop setpoints and outputs.

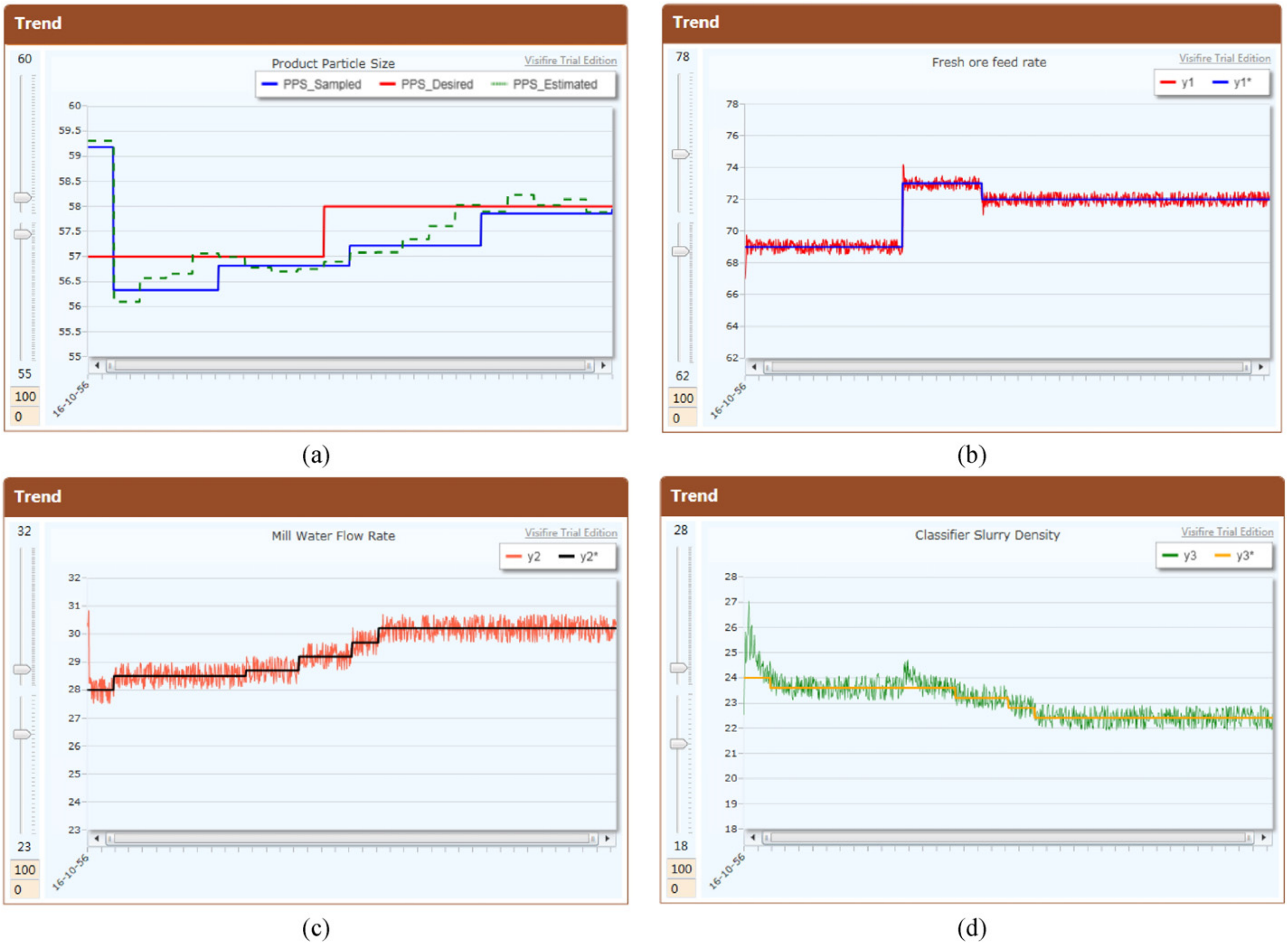


Fig. 18. Control trends when the desired PPS changed: (a) PPS; (b) fresh ore feed rate; (c) water flow rate of the ball mill; (d) slurry density of the spiral classifier.

experiment is essential to verify the dynamic performance of control system. The dynamic response of PPS and control loops are shown in Fig. 18. From it, one can obtain that when the desired PPS has been changed, the controller can recognize the deviation of PPS at once, and then adjust the setpoints accordingly. With the help of the basic loop control system, the actual PPS can be controlled in the vicinity of its target value again after 7 control periods.

Via the above experiments, the effectiveness of the HILS platform has been validated. The above mentioned supervisory control scheme is just one that has been developed and tested by us, and other algorithms for different grinding process also can be implemented and tested in the proposed HILS platform.

6. Conclusion

Motivated by the problem of the design and testing of supervisory controller of mineral grinding processes, a HILS platform is developed. The HILS platform can not only provide a full-scope simulation environment for the MGP by developing the software and hardware of virtual plant system as well as virtual actuator and sensor system, but also enable the design of the supervisory control system by developing the software and hardware of supervisory controller and embedded soft PLC (ES-PLC)-based loop controller. The above efforts make the HILS platform close to the real industrial system, which is not possible in the currently available COTS simulation packages. A case study about an intelligent supervisory control method for a typical MGP is presented to validate the effectiveness of the HILS platform. The study result shows that a new supervisory control method can be designed and tested before practical application with the developed HILS platform, which is useful for reducing the risk of damage to operating devices, and increasing the rate of qualified production. Though the HILS platform is intended for the testing of supervisory control algorithms for the MGP, it can be easily modified to test the supervisory control system for some other resource-intensive industrial processes.

Acknowledgments

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