A distributed model predictive control with machine learning for automated shot peening machine in remanufacturing processes

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Abstract
In practical peening operation, the values of inlet air pressure and media flow rate are manually preset to acquire desired intensity requirements. The operator often needs to perform intensive experimental trials to determine a set of operational inputs for actual production. Obtaining these operational parameters is often time-consuming and labor-intensive. Thus, in this study, we propose an optimal distributed model predictive control for the multiple input/multiple output system to address the issues. In the newly developed system, control actions of inlet air pressure and voltage are optimally obtained with the anticipation of the predictive future states of the plant models, while reference values of air pressure at the nozzle and media flow rate are determined using a proxy model. The dynamical plant models include an air pressure model and a media flow rate model, which are developed based on measurement data and physics-based knowledge using the sparse identification of nonlinear dynamics algorithm. The proxy model is developed from the measurement data of the intensity, pressure, and media flow rate using a deep machine-learning algorithm. The control performance is demonstrated using on-site controls at the physical machine for different operational scenarios. The obtained measurement results exhibit a favorable control performance in stability, robustness, and accuracy. The measurement intensity is consistent with the target setting value; the difference is smaller than the industrial threshold of ± 0.01 mmA for all random tests. In another word, all target setting intensity can be achieved without the need of performing trials to determine the operational parameters. It also suggests that the developed control system can be deployed to the physical machine for actual production.

Keywords MIMO control system · Model predictive control · Smart shot peening machine · Data model · Machine learning · Distributed MPC

1 Introduction
The shot peening process is a well-known technology in the remanufacturing industry that enhances the surface condition of the new or old components for lasting longer service life [1–3]. The shot peening process creates a thin compressive layer on the surface of the treated component that can against the corrosion, fatigue life cycle, and effects of micro-crack [4]. Intensity is one of the two outcome parameters of a peening process that represents the kinetic energy of the media flow transferred to the surface of the component. The operator often measures the peening intensity via the Almen strip by constructing the saturation curve [5–7]. A set of operational parameters (such as inlet air pressure, media flow rate, media type) is manually pre-set to achieve a certain value of the intensity in actual production [8, 9]. However, the determination of this set of parameters is a challenging task, as it often requires intensive experimental trials. In addition, different parts of a treated component might also require different intensities as well. As a result, the determination of operational parameters can be time-consuming, cost-expensive, and material waste. From another perspective, machine learning (ML) has been widely applied to develop the control system design in advanced manufacturing processes [10–13]. Therefore, a deep and tight combination of the model predictive control (MPC)
and ML can properly offer a promising solution for a smart and fully automated process in the advanced manufacturing operation. Smart and advanced manufacturing has become a hot research topic recently. In particular, for peening operation, the huge amount of historical data generated in actual operations and trials with physics background knowledge can be useful for model development in the model-based control system design (e.g., AI or ML model [14, 15], empirical process model [16, 17]).

In the previous study, we proposed a single-input/single-output (SISO) MPC with a proxy model to partially automate the shot peening operation based on controlling inlet air pressure [10]. More specifically, the proxy model was developed from a set of historical data using the extreme gradient boosting (XGBoost) ML algorithm [18] to translate the desired intensity to an air pressure reference set point at the nozzle [14, 15]. The process model that links the inlet air pressure to the air pressure on the nozzle was developed and deployed in the SISO MPC controller to automatically drive the dynamical process of the peening system to the reference set point, as such; the desired intensity is achieved [14]. This proposed technology, however, is still not an optimal solution as it only performs control action based on inlet air pressure, while the media flow rate still needs to be pre-set and heavily relies on the operator’s experiences. Thus, in this study, we extend our previous work for multiple input/multiple output (MIMO) MPC to control both inlet air pressure and media flow rate of the peening machine to provide a better solution for fully automated operation.

Particularly, in this study, we consider the distributed model predictive control where the information can exchange among sub-processes locally but without solving a centralized MPC problem, to design MPC for a smarter shot-peening machine. Our objectives are to (1) inherit the good work of our previous development of SISO MPC for controlling the air pressure [14], (2) apply the same methodology to develop the controller for media flow rate, and (3) develop sub-models that count on influences of the future change in the air pressure to media flow rate model and vice versa. In addition, the distributed MPC approach is useful as the local optimization problems can be much smaller than a centralized problem: thus, it can help to speed up the computational time to achieve real-time control [19]. The details of development works are shown in the following subsequence sections. The paper is organized into eight sections. Section 1 is the introduction and motivation of the current work. Section 2 is the general form of distributed model predictive control problem and application to this study. Section 3 shows the experimental setup for data collection to build the models. Section 4 describes the process and proxy model development. Section 5 is the design of distributed model predictive controller architecture. Section 6 expresses the control performance and refinement process. Section 7 is the on-site control demonstrations. Finally, Sect. 8 summarizes the contents of this study.

## 2 Distributed model predictive control

In this study, the distributed model predictive control approach is considered for the design of MIMO MPC to control the outputs of media flow rate and air pressure on the nozzle by manipulating the inlet air pressure and the voltage at the media valve. In the general form of model predictive control, the control actions $u(k)$ at the time step $k$ are evaluated by solving the optimization problems of the following form:

$$
\min_{X(k), U(k)} J(X(k), X^{ref}(k), U(k))
$$

In this expression, $X(k)$ is a vector of the state variables of the dynamical systems. $X^{ref}(k)$ is a vector of the reference states of control set points. $U(k)$ is a vector of the manipulated variables. They are expressed as follows:

$$
X(k) = \{x(k+1), \ldots, x(k+N)\}
$$

$$
X^{ref}(k) = \{x^{ref}(k+1), \ldots, x^{ref}(k+N)\}
$$

$$
U(k) = \{u(k), \ldots, u(k+N-1)\}
$$

Subject to the following process models and constraints:

$$
X(k+i+1) = F(X(k+i), U(k+i)) (i = 0, \ldots, N-1)
$$

$$
G(X(k), U(k)) \leq 0
$$

$F(x, u)$ is the process model that is used to predict the future state $(k+i+1)$ of the physical system based on the information at the previous state $(k+i)$. The constraints, $G(X(k), U(k))$, represent the physical limits and/or the stability and robustness of the system.

In the distributed model predictive control, the system in Eqs. (1)–(6) is described in multiple subsystems. Each subsystem is expressed using a specific process model with local variables and relevant constraints. The objectives of this decomposition are that (1) the subsystem is much smaller than the original problem and (2) the subsystem only couples to a few state reference variables for tracking. Following is the optimization problem of the sub-systems:

$$
\min_{X_m(k), U_m(k)} J(X_m(k), X^{ref}_m(k), U_m(k))
$$

Subject to:
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G_m(X_m(k), U_m(k)) ≤ 0

(9)

H_m(X_m(k), U_m(k)) = 0

(10)

In this expression, F_m(x_m, u_m) is a local process model. G_m(X_m, U_m) is the local operational constraints. H_m(X_m(k), U_m(k)) is the function that interacts with other subsystems.

For the shot peening application, the distributed MPC system is decomposed into two subsystems, which are the air pressure and media subsystem. The air pressure subsystem includes an air pressure regulator, a pressure sensor at the inlet, and a pressure sensor at the nozzle. The process model (F_1) for this subsystem links the pressure at the nozzle to the inlet air pressure with the pressure regulator as a manipulated variable. This development work is inherited from the previous study [14]. The media flow rate subsystem includes a media valve, an input voltage sensor, and an output voltage sensor. The applied voltage at the inlet is controlled to open the media valve based on the opening percentage. The actual media flow rate released into the system is evaluated via the value of the voltage at the outlet. The model (F_2) for this subsystem links the inlet voltage and outlet voltage (media flow rate). A function (H_1) counts on the effect of the pressure change on the media flow rate and vice versa (H_2). These process models are developed based on the experimental data and physics background knowledge of the multiple-phase flow using the sparse identification of the nonlinear dynamics algorithm (SINDy) [20, 21]. Details of the model development and controller design are shown in the following sections.

3 Experimental setup and data collection

This section focuses on the experimental setup of the shot peening machine and data collection of the relevant variables to build both the process models and proxy models. The process models link the manipulated variables to the controlled (or observed) variables that use for model-based controller development, while the proxy model translates the statistical peening intensity to the reference set points for real-time tracking during process control operation.

3.1 Experimental setup

Figure 1 shows the schematic diagram of the experimental setup of the Abrasive Engineering (AE) physical robotize shot peening machine on our shop floor in Advanced Remanufacturing and Technology Centre (ARTC), A*Star, Singapore. The main components of the experimental system include a pressure sensor at the inlet, a pressure sensor at the nozzle, a pressure regulator, a voltage sensor at the inlet, a media flow rate sensor, a media flow regulator, an MPC controller, a robot arm, a hose system, a nozzle, Almen strip holder, and Almen strips. In particular, the piezoresistive pressure sensors (from KISTLER) are mounted at the inlet (P1) and nozzle (P2) to measure the manipulated air pressure and monitored air pressure for closed control, respectively. The experimental trials utilize a single straight bore peening nozzle with an internal diameter of 14.0 mm for representing the actual operation. The Abrasive media flow microwave valve with the measurement range from 0.0 to 5.0 kg/min corresponding with the input voltage range from 0.0 to 10.0 V is utilized to control the media flowrate feeding to the system based on the signal sent by the MPC controller. The media flow rate sensor measures the actual media flow rate in real time for feedback control. The ABB robot arm controls the tool path (nozzle) to follow specified trajectories. The in-house designed Almen strip holder can hold up to eight Almen strips on both sides to build a saturation curve.

3.2 Design of communication protocol for control system

Figure 2 shows the design of the communication protocol for sending and receiving data for closed-loop control. In this design, the system runs off a workstation that hosts the developed MPC software and controls the shot peening machine through the DAQ device. The air pressure is controlled via an open platform communication–unified architecture (OPC-UA) to the pressure regulator. The media flow rate is controlled via analog voltage sent to the flow master which is an intermediary device required to communicate with the media valve. The range of analog voltage is from 0.0 to 10.0 V that is corresponding to the opening of the

\[
X_m(k+i+1) = F_m(X_m(k+i), U_m(k+i)) \quad (i = 0, \ldots, M - 1)
\]

\[
G_m(X_m(k), U_m(k)) \leq 0
\]

\[
H_m(X_m(k), U_m(k)) = 0
\]
valve from 0 to 100%. A digital signal is established between the ABB robot controller and DAQ for the detection of the position of the robot tool in the peening sequence. The air pressure sensors P1 and P2 measure the pressure at the inlet and nozzle, respectively, and return the values back to the system for closed-loop control of air pressure. In the media valve, the magnetic sensor returns an analog voltage in the range of 0.0–10.0 V and a frequency of 256 Hz to the system for the closed-loop media flow control. The feedback signal is in the range of 0.0–10.0 V corresponding to the range of media flow rate of 0.0–5.0 kg/min.

### 3.3 Data collection for process model development

To build two separate process models for the distributed model predictive control, the experimental conditions are listed in Tables 1 and 2 for data collection. The parameters in Table 1 are to develop the process model for linking the inlet air pressure to the pressure at the nozzle, while the parameters in Table 2 are for the development of inlet voltage and media flow rate. To collect data for media flow model development, four experiments were carried out for four fixed values of the inlet air pressure (0.138, 0.207, 0.310, and 0.372 MPa or 20.0, 30.0, 45.0, and 54.0 psi) for each media type (ASR70 and ASR230). For each experiment, the voltage applied to the media valve increases from 0.0 to 10.0 V; it then decreases back to 0.0 V with a step of 0.25 V to measure the inlet voltage and media flowrate at each sample time. Other parameters are fixed at constant values (refer to Table 1 for details). Similarly, to collect data for pressure model development, five experiments corresponding to five values of fixed media flowrate are performed for each media type. For each experiment, all parameters are fixed, while only inlet air pressure increases from 0.0 to 0.372 MPa and then decreases from 0.372 back to 0.0 MPa with a constant step of 0.014 MPa (or 2 psi) to measure the inlet air pressure and pressure at the nozzle at each sample time (see reference [14] for more details).

Figure 3a shows the measurement data of the media ASR 70 type with a fixed inlet air pressure of 0.207 MPa and varying inlet voltage, while Fig. 3b shows the measurement data of the media ASR 70 type with a fixed media flow rate at 3.0 kg/min and varying inlet air pressure from 0.0 to 0.372 MPa. In general, the observation indicates that the opening percentage (%) of the valve (or inlet voltage) is smaller for achieving the same media flow rate as the inlet air pressure increases. The change in media flow rate also slightly affects both air pressure at the inlet and at the nozzle although we set a fixed value of the air pressure at the input. The measurement signals become noisier as the media flowrate and/or air pressure is higher.

### 3.4 Data collection for proxy model development

To collect data for proxy model development, two similar sets of experiments for two media flow types (ASR 70 and ASR 230) are set up and performed to measure the air pressure on the nozzle, media flow rate, and peening intensity. For each peening nozzle, five different values of media flow rate (of 1.0, 2.0, 3.0, 4.0, and 5.0 kg/min) are set for each value of the inlet air pressure (0.138, 0.207, 0.310, and 0.372 MPa) to form 20 experimental peening conditions. Similar to previous work, each operation condition is performed for at least four different exposure times to develop a saturation curve to determine one value of the peening intensity. Each value of the peening intensity is also performed two times to ensure that the measured intensity is accurate (error ±0.01 mmA (industrial threshold)) and repeatable. The values of air pressure and media flowrate are chosen within the operational windows of the selected physical shot peening machine. In addition, the standoff distance and peening angle are selected based on actual operation at 120 mm and 70°, respectively. The intensity is measured

| Table 1 | Experimental setup for increase and decrease of the voltage at the inlet of media flowrate valve |
|---------|-------------------------------------------------------------------------------------|
| Experimental parameter | Value |
| Media type | ASR 70 | ASR 230 |
| Impinging angle (deg°) | 70.0 |
| Stand-off distance (mm) | 120.0 |
| Air pressure (MPa) | 0.138, 0.207, 0.310, 0.372 |
| Voltage at the inlet of the valve (V) | 0.00:0.25:10.00 |

| Table 2 | Experimental setup for increase and decrease of the air pressure at the inlet |
|---------|--------------------------------------------------------------------------------|
| Experimental parameter | Value |
| Media type | ASR 70 | ASR 230 |
| Impinging angle (deg°) | 70.0 |
| Stand-off distance (mm) | 120.0 |
| Media flow rate (kg/min) | 1.0, 2.0, 3.0, 4.0, 5.0 |
| Air pressure (MPa) | 0.00:0.014:0.372 |
using Almen gage to obtain the arc height of the processed Almen strip type A. Refer to reference [6] for the details of the measurement standard procedure. Figure 4 shows the measurement intensity versus the media flow rate and pressure on the nozzle for different operational conditions. It is clear that the intensity is higher as the air pressure is higher, while it is lower as the media flow rate is higher.

4 Model development

In this study, we develop the distributed model predictive control for the current physical shot peening machine. Two distributed controllers will control sub-systems in the peening operation, which are modeled by two process models (plant models), to meet the reference set points.

4.1 Process model development

In this subsection, the sparse identification nonlinear dynamical system (SINDy) algorithm [20, 21] is utilized to develop two separate process models for the development of the distributed model predictive control in the subsequence section. The first process model is developed to link the manipulated inlet air pressure to the monitored air pressure at the nozzle. The second process model links the manipulated input voltage to the monitored media flow rate. In this approach, the sparse coefficients of the relevant candidate functions in the functional library are obtained by solving the sparse regression problem with measurement data. The functional library is selected using the physical background knowledge of the multiple-phase flow problem.

To develop the control system, we assume that the process (plant) model has the following form:

\[
\frac{dx}{dt} = f_p(x) + f_m(x) + g(u)
\]

In this form, \(x\) is the process variables, which are the air pressure at the nozzle and media flow rate at the flow master. \(u\) are the manipulated variables, which include the inlet air pressure and voltage applied to the inlet of the media valve. \(f_p(x)\) is the state function for air pressure, while \(f_m(x)\) is the function that counts on the effect of media flow rate on the pressure function, and inversely. \(g(u)\) is the trigger function of the input air pressure or the voltage applied at the inlet of the media valve; it can include both linear and nonlinear functions. In this study, the measured data in Sect. 3.3 is arranged in column vectors with time series to be used in the SINDy algorithm to obtain the process.
model coefficients (see Fig. 5 below). Refer to references [14, 20, 21] for SINDy algorithm details.

The obtained air pressure process model is then validated with measurement data for the same inlet air pressure within fixed 5 media mass flow rate values (1.0, 2.0, 3.0, 4.0, and 5.0 kg/min), while the media flow rate process model is also benchmarked with measurement of the fixed 4 inlet air pressure values (0.138, 0.207, 0.310, and 0.372 MPa). Figure 6 shows the comparisons of the obtained process model outputs with the experimental data; Fig. 6a is the process model of air pressure for a fixed media flow rate of 3.0 kg/min, while Fig. 6b is the process model of the media flow rate for fixed inlet air pressure of 0.310 MPa. The obtained results indicate that the process models of both the air pressure and media flow rate obtained by the SINDy algorithm can accurately represent the dynamical processes of the shot peening for the full operational windows. These two process models are then used to develop the sub-controller in the distributed control system.

### 4.2 Proxy model development

In this section, the proxy model is developed to evaluate the reference set points of the air pressure on the nozzle and media flow rate from the desired intensity, media size, exposure time, and peening coverage information. Similar to the previous study [14], the proxy model is developed using the measurement data of the pressure sensor on the nozzle, media flow rate, media size, peening exposure time, and peening intensity for different operating conditions using XGBoost machine learning algorithm [18]. The XGBoost in Python language is a scalable end-to-end tree boosting system. In which, the sparsity-aware algorithm is used for handling the sparse data. The weighted quantile sketch is employed for approximating the tree learning. In addition, the software package also provides data compression, cache access patterns, and sharing to build a scalable tree boosting system. Refer to reference [18] for details of the algorithm.
In this study, besides the set of the media flow rate, operating inlet pressure, media size, pressure at the nozzle, and peening intensity, both the exposure time and peening coverage are also recorded. The extra information (peening coverage and exposure time) is employed for predetermination of the required media flow rate based on the developed formulation in reference [22]. In particular, the coverage area is expressed as \( C\% = 100\left(1 - \exp\left(-\sum_{i=1}^{N} a_i/A\right)\right) \). In this expression, \( C\% \) is the coverage area, and \( A \) is the treated surface area. \( a_i \) is the dimple size created by the impaction of the media on the component surface. \( N \) is the number of impaction (or the number of the hit of peen on the treated surface). \( N \) can be described as a function of media flow rate \( (m) \) and exposure time \( (t) \) as \( (N = 3mt/(4\pi \rho_p d_p^3)) \). \( \rho_p \) is the density of the media flow, while \( d_p \) is the diameter of the media. Physically, the information of the input air pressure, media flow rate, and media size determines the value of the peening intensity. Air pressure at the nozzle could be an indicator of the flow stream energy; therefore, the pressure at the nozzle is used to monitor to ensure that the setting intensity is achieved. Refer to reference [14] for details of model training using the XGBoost ML algorithm.

Figure 7 shows the comparison of the prediction of the proxy model with the measurement data for the same operating conditions; Fig. 7a is for ASR 70 and Fig. 7b is for ASR 230 (right), respectively. It can be seen that the estimated values of proxy model are comparable to the measurement value for the same operational inputs. It implies that the proxy model is able to predict the pressure at the nozzle with the input of the target intensity, reference media flow rate, and peen size. Both the obtained value of air pressure at nozzle and media flow rate (evaluated using reference [22]) will be used as the reference set points for the feedback control.

5 Control system architecture design

As mentioned, the distributed model predictive control technology approach is employed to design the control system for the current shot peening machine to manipulate the air pressure regulator and media valve in a specified sequence. Figure 8 shows the design of the distributed MPC control logic, while Table 3 shows the control algorithm for the working sequence of the design distributed MPC. In peening operation, the operator inputs the desired value of the peening intensity to the machine. The proxy model then converts this intensity value to reference set points of the air pressure at nozzle and media flow rate. In Fig. 8, the “Ref1” is the reference set point of the air pressure on the nozzle, while the “Ref2” is the reference set point of the media flow rate. “Process model 1” describes the relationship between the inlet air pressure and air pressure on the nozzle. “Process model 2” links the input voltage to media flow rate. “u1” is the control value that is sent to the pressure regulator at the
inlet, while “u2” is the control value of the input voltage that is sent to the media valve. The shot peening machine (SPM) is the physical shot-peening machine. “m1” is the measurement value of air pressure on the nozzle and “m2” is the measurement value of the media flow rate.

6 Control performance and refinement

In this section, we perform the on-site control experiments for different scenarios of the change in both reference set points of the media flow rate and air pressure at the nozzle to test the performance of the designed control system in compensating for any abrupt change and disturbance. The changes in the reference set point include the abrupt increase and decrease in either air pressure or media flow rate or both. In these experiments, the ASR 230 media type is chosen as the size of the media is bigger, and the bigger size of the media often causes more instability compared to the smaller size. Thus, the control performance will be stable for the smaller media size if it is stable with the bigger size. To study the control performance, we measure the voltage at the inlet of the media valve, actual media flow rate, inlet air pressure, and air pressure on the nozzle during the experiments. There is no Almen strip used in these experiments. Figures 9, 10 and 11 show the control performance of the different cases with the change of either air pressure or media flow rate, or both air pressure and media flow rate. In these figures, the green line is the voltage (in V) at the inlet of the media valve. The black dashed-dot line is the reference set point of the media flow rate (in kg/min), while the purple line is the measurement value of the media flow rate (in kg/min). The blue line is the inlet air pressure (in MPa). The black dashed line is the reference set point of the air pressure (in MPa) on the nozzle, while the red line is the measurement value of the air pressure (in MPa) on the nozzle.

Figure 9 shows the plots of the control performance for the cases with the changes in pressure reference set point. Figure 9a is the case of the abrupt increment of the air pressure jumping from 0.1 to 0.25 MPa (case 1), while Fig. 9b is the case of the abrupt decrement of the air pressure jumping down from 0.24 to 0.10 MPa (case 2). The reference value of the media flow rate is fixed at 3.0 kg/min. There is a disturbance in the media flow rate measurement as the air pressure starts changing in both

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**Table 3 Control algorithm for working sequence of the distributed model predictive control for shot peening machine**

| Control algorithm: Distributed MPC for smart shot peening machine |
|---------------------------------------------------------------|
| **Step 1:** Evaluate the reference new set-points |
| • Operator keys in new peening intensity |
| • Solve proxy model for reference set-points of air pressure on nozzle and media flowrate |
| • Update reference set-points at corresponding controllers |
| • Move to step 2 |
| **Step 2:** Process control in sequence |
| • Update measurement data of both air pressure on the nozzle and media flow rate |
| • Solve the objective function of the air pressure with process model 1 for u1 |
| • Update control action (u1) to the process model 2 and controllers |
| • Solve the objective function of the media flow rate with process model 2 for u2 |
| • Send both control actions u1 and u2 to the inlet pressure regulator and media valve for adjustment |
| • Update measurement data with new control action u1 and u2 |
| • Repeat the process till the process is complete or change the peening intensity |
| **Step 3:** Return to step 1 or stop the production process |

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![Fig. 9 Testing performance of the control system to compensate for the abrupt change of the reference set point of the air pressure](image-url)
cases. It means that the media flow rate is very sensitive to pressure change. However, the controller immediately stabilizes it and drives it back to the normal value in case 1, while the pressure regulator continues to drive the inlet air pressure gradually to the new reference set point in both cases. The plot also shows that a higher air pressure reference requires a significantly lower voltage at the inlet of the media valve to maintain the fixed set point of media flow rate, and vice versa. In case 2, the media flow rate increases as the inlet air pressure decrease even though the media valve is gradually forced to close by the controller. In this case, the media flow rate gradually increases and reaches the maximum value (at 5.0 kg/min) and only returns to the set point when the pressure is stable at the reference value. Because the actual media flow rate is more sensitive to the pressure difference than the valve opening level (or voltage applied at the inlet). To maintain the reference value of the media flow rate, the controller must respond faster to close and open the valve according to the change of the pressure; however, the control and system stability need to be accounted for. In fact, we choose the system stability in the controller design.

Figure 10 shows the results of the control performance for the case with the change of the reference set point of media flow rate. Figure 10a is the increment of the media flow rate from 2.0 to 3.75 kg/min (case 3), while Fig. 10b is the decrement of the media flow rate from 3.0 to 1.5 kg/min (case 4). The pressure value is fixed at 0.10 MPa for both cases 3 and 4. The obtained results show that the designed controller takes a long time (about 50 s) for the media flow rate to attain and stabilize at the set-point value, while the air pressure regulator only makes a small adjustment to maintain the reference value. It should be noted that the higher step-change in reference value of the media flow rate often takes a long time to attain and stabilize. The plots indicate that the air pressure is less sensitive to the change in the media flow rate. However, a small change in air pressure is adjusted to compensate for the change in the media flow rate; as a result, the reference set point of the air pressure is maintained.

Figure 11 shows the control result of the case with the abrupt change in both media flow rate and air pressure. The air pressure changes from 0.10 to 0.175 MPa, while the media flow rate increases from 2.0 to 3.0 kg/min (case 5). The results show that the air pressure is quite stable during the transition from the old reference set point to a new reference value, while the media flow rate gets a small overshoot before reaching the stable state. In general, the performance of the distributed MPC is quite stable and accurate. It means that the designed distributed MPC can bring the system dynamics to the new state stably and accurately.

7 On-site production demonstration

This section shows the results of process control variables and measurement intensity from the onsite control demonstrations. Four different extreme scenarios, which cover most of the critical cases of the current shot peening operation, are used to demonstrate the performance of the developed control system. The four cases are, namely, “case 6,” “case 7,” “case 8,” and “case 9.” In “case 6,” the setting intensity is 0.375 mmA, while the estimated media flow rate for 98% peening coverage is about 4.6 kg/min. In “case 7,” the setting intensity is 0.355 mmA, and the media flow rate for 98% peening coverage is about 3.0 kg/min. In “case 8,” the setting intensity is 0.310 mmA, and the media flow rate for 98% peening coverage is about 2.3 kg/min. And “case 9,” the setting intensity is 0.280 mmA, and the media flow rate for 98% peening coverage...
is about 3.3 kg/min. It should be noted that the value of 98% peening coverage is a threshold for satisfaction in industrial peening operations. In addition, in this study, the chosen value of peening coverage must be smaller than 100% to be valid with the formulation in the reference [22]. Thus, we choose the value of 98% coverage area for the mass flow rate evaluation. The proxy model translates the setting intensity and media flow rate into the reference set points of the air pressure at the nozzle and the media flow rate, respectively. Similar to the previous section, the ASR 230 media type is used in these on-site demonstrations. The standoff distance is 120 mm, and the peening angle is 75°. Four different nozzle transition speeds (or peening time) are pre-set for four Almen strips to build the saturation curve. Each test is repeated two times to ensure repeatability. There is no test case that has failed as all differences in the arc height of the pair are smaller than the requirement of 0.005 mmA.

Figures 12, 13, 14 and 15 show the onsite control performances (a) and saturation curves (b) for extreme cases of different target settings of peening intensity and peening coverage of 98%. In the control performance plot, the yellow line is the input voltage (in V). The black line is the reference set point of the media flow rate (in kg/min). The purple line is the measurement value of the media flow rate (in kg/min). The blue line is the inlet air pressure (in MPa). The dashed and black line is the reference set point of the air pressure at the nozzle (in MPa). The red line is the measurement value of the air pressure at the nozzle (in MPa). In the saturation curve plot, the blue line is the saturation curve. The red lines indicate the arc height at exposure time (1 T), while the green lines show the arc height (saturation value) at 2 T. Refer to reference [6] for the detailed meaning of the saturation curve and all parameters. The obtained results show that the pressure control has a shorter delay time compared to the...
media flow rate control. The pressure takes about 10 to 25 s to stabilize, while the media flow rate takes about 50 to 120 s depending on the value of the reference set point. The higher value of the reference set point often takes a longer stabilizing time. For better peening quality, the actual peening can only start as the media flow rate reaches and stables at the reference set point. In all cases, both pressure and media flow rate control performances are accurate and stable.

In addition, for all cases, the measurement intensities are very close to the corresponding target setting values. The maximum difference between the obtained intensity and setting value is smaller than the industrial threshold (±0.01 mmA). Figure 12 shows the measurement intensity of 0.377 mmA, while the setting value is 0.375 mmA. The difference is only 0.002 mmA for “case 6.” Fig. 13 shows the obtained intensity at 0.356 mmA and the setting value at 0.355 mmA. The difference for “case 7” is only 0.001 mmA. Figure 14 shows the measurement intensity at 0.305 mmA and setting intensity at 0.310 mmA. Therefore, the difference of “case 8” is about 0.005 mmA. Similarly, Fig. 15 shows the measurement intensity at 0.280 mmA and the setting intensity at 0.280 mmA. There is no difference in intensity for “case 9.” It implies that the designed control system is robust and accurate. In another word, the developed control system meets the industrial requirements for actual production; thus, it can be deployed in industrial production site to improve quality, efficiency, and productivity. In another word, this distributed MPC can also help to reduce the cost, time, and material waste of the existing shot peening machine in production operation.
8 Conclusions

In this paper, a distributed MIMO model predictive control is developed and deployed at the physical shot peening machine to upgrade the existing SISO model predictive control system from our previous work to provide the optimal control action for both air pressure and media flow rate. The distributed control system is developed based on two subprocess models of air pressure and media flow rate. The process models are developed using SINDy algorithm, while the proxy model is developed using the XGBoost machine learning algorithm. The sub-controllers follow a working sequence to count on the effect of the media flow rate on air pressure, and vice versa.

The newly developed control system is also demonstrated and validated using onsite controls with different scenarios for process control performance. The measurement data reveals good control properties in stability, accuracy, and robustness. Onsite controls are also benchmarked for different actual production scenarios, which are set up to cover the whole range of the practical peening operations. The developed control system can therefore be directly deployed to the current shot peening production, as such reducing the dependency on the Almen system. This in turn will help to reduce the material waste, time, labor, and cost associated with the development of the saturation curve.

In terms of next steps, online machine learning techniques for optimal model predictive control that are promising approaches for controller development and design will be explored. This combination can enable a more robust, accurate, and scalable control system for large-scale and complex dynamical processes. Three possible approaches include (1) using the machine learning techniques to develop the process model(s) with online learning capability for controller development, (2) using the machine learning to learn and improve the control policies online, and (3) developing a machine learning algorithm with model predictive control being a part of the algorithm.

Author contribution Van Bo Nguyen: developed the framework for obtaining process models and proxy model, analyzed data and develop the process models and proxy model, and the control system using distributed MPC, refined both process models and controller, performed all control scenarios for validation and demonstration, developed ideas for this paper, analyzed data, wrote original, and revised paper. Augustine Teo: design experiments, performed experimental trials, analyzed data, and revised paper. Chang Wei Kang: managed and provided direction for research development, provided ideas on control design, and revised paper.

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Availability of data and material (data transparency) The authors will make availability of any related data to this manuscript if requested (or data will available on request).

Declarations

We confirm that this paper is original and has not been published elsewhere nor is it currently under consideration for publication elsewhere.

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