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A hybrid machine learning method to determine optimal operating process window in aerosol jet 3D printing

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ABSTRACT–Aerosol jet printing (AJP) is a 3D non-contact and direct printing technology for fabricating customized microelectronic devices on flexible substrates. Despite the capability of fine feature deposition, the complicated relationship between main process parameters will affect the printing quality significantly in a design space. In this paper, a novel hybrid machine learning method is proposed to determine optimal operating process window for AJP process in various design spaces. The proposed method consists of classic machine learning methods, including experimental sampling, data clustering, classification and knowledge transfer. In the proposed method, a 2D design space is fully explored by a Latin hypercube sampling experimental design at a certain print speed. Then, the influence of sheath gas flow rate (SHGFR) and carrier gas flow rate (CGFR) on the printed line quality is analyzed by a K-means clustering approach, and an

optimal operating process window is determined by a support vector machine. To efficiently identify more operating process windows at different print speeds, a transfer learning approach is applied to exploit relatedness between different operating process windows. Hence, at a new print speed, the number of line samples for identifying a new operating process window is greatly reduced. Finally, to balance the complex relationship between SHGFR, CGFR and print speed, a 3D operating process window is determined by an incremental classification approach. Different from experiment based approaches adopted in 3D printing technologies for quality optimization, the proposed method is developed based on the theory of knowledge discovery and data mining. Therefore, the knowledge in different design spaces can be fully explored and transferred for the printed line quality optimization. And, the data-driven based characteristics can help the proposed method develop a guideline for quality optimization in other 3D printing technologies.

KEYWORDS: aerosol jet printing, direct writing, hybrid machine learning, line morphology, operating process window, quality optimization

1. Introduction

Direct writing is a promising additive manufacturing technology to fabricate customized, low cost, conformal devices and electronic circuits on flexible substrates.¹⁻³ In recent years, a variety of direct writing methods such as screen printing,⁴⁻⁶ inkjet printing,⁷⁻⁹ and aerosol jet printing (AJP)^{3,10} have been extensively studied and adopted to print electronic components and sensors. Compared with inkjet printing and screen printing, AJP is a newly developed approach for printing microelectronics on the flexible substrates. Due to its flexibility and high resolution, there has been

increasing interest in using this technique for printing conductors, semiconductors, and dielectrics, including electrode arrays,¹¹ transistors,¹²⁻¹⁶ strain gauges and solar cells.¹⁷⁻²⁰

As the printed line quality greatly affects the performance of fabricated electronic components, the conductive line is an important element for AJP. The conductive line printed discontinuity is the main reason of open circuit in aerosol jet fabricated components. And, high overspray of AJP is detrimental to the narrow-spaced lines and could cause the risk of short circuit between lines. In addition, the edge roughness of conductive line has a decisive influence on the homogeneity of the printed line resistance, which is critical for resistive sensors.²¹⁻²⁷

As process parameters have complicated impact on the printed line morphology, especially the interaction between different process parameters aggravates the impact on the printed line morphology dramatically. To fabricate continuous lines with better edge definition and lower overspray, it is crucial to identify an operating process window for quality optimization in AJP. However, most printing works are operated at low speeds (especially 1 mm/s) and determine the appropriate process parameters manually, which relies on personal experiences and the printed line morphology lacks further investigation in the remaining design space. Therefore, it is necessary to sufficiently explore a design space and optimize the printed line morphology systematically.

The line morphology of AJP is affected by different types of factors, such as process parameters, ink properties and substrate treatment methods.^{23, 26, 28} Among these factors, sheath gas flow rate (SHGFR), carrier gas flow rate (CGFR), and print speed are three important adjustable parameters during the printing process.^{21, 29, 30} To investigate the effect of these three factors on the line edge definition,^{23, 26, 27} the edge roughness of the printed line is defined to evaluate the printed line quality. Despite these studies enabling the reduction of printed line edge roughness, they were limited to

certain low print speeds and the design space was investigated insufficient. Besides line roughness, the aspect ratios (thickness/width) was also proposed to optimize the line morphology,^{21,24,26} and an optimal operability window was determined experimentally to fabricate tall and narrow lines. The proposed operating window was advantageous to optimize printing quality, however, the printed line quality lacked quantitative analysis and the exploration of a 3D design space was insufficient as the ratio (SHGFR/CGFR) was kept constant.

In this paper, a novel hybrid machine learning method is proposed to determine optimal operating process window for AJP process in various design spaces. The proposed method consists of classic machine learning approaches, including experimental sampling, data clustering, classification and knowledge transfer. A 2D design space is explored by a Latin hypercube sampling experimental design at a certain print speed. And, the printed line morphology distribution is analyzed by a K-means clustering, and an optimal operating process window is determined by a support vector machine. In addition, a transfer learning approach is adopted to efficiently determine more operating process windows at different print speeds. Finally, to balance the complex interaction between SHGFR, CGFR and print speed, a 3D operating process window is determined by an incremental classification approach. Different from experiment based approaches adopted in 3D printing technologies for quality optimization, the proposed approach is developed based on the theory of knowledge discovery and data mining. Therefore, the knowledge in different design spaces can be fully explored and transferred for printed line quality optimization.

The rest of the paper is organized as follows. Experimental methods and theoretical basis are described in Section 2. Section 3 discusses the experimental results of printed line quality and

identified operating process windows. Finally, conclusions and future research directions are presented in Section 4.

2. Experimental methods and theoretical basis

In this section, experimental setup and the printed line feature extraction are described, and the theoretical basis of the adopted classical machine learning approaches is presented in the next.

2.1 Experimental setup

In this research, an ultrasonic atomizer was utilized for AJP, and a schematic to describe the AJP process is demonstrated in Figure 1. In this technique, the nanoparticle conductive ink is atomized into aerosol droplets and entrained by a nitrogen carrier gas flow, then a nitrogen sheath gas flow enwraps the aerosol stream cylindrically in the print head. As the aerodynamic interaction in the print head, the aerosol stream exits the print nozzle with high velocity, and a fine line is printed onto the moving substrate.

A silver conductive ink (Clariant) mixed with deionized water (1:1 by volume) was adopted as functional ink in this research. The ink temperature was kept at 20 °C. The current of the ultrasonic atomizer was set as 0.3 mA and a nozzle with the tip diameter of 150 μm was chosen to print at the height of 4mm. SHGFR (15 to 150 sccm), CGFR (15 to 50 sccm) and print speeds (1 to 10 mm/s) were varied to print a single pass of line onto polyimide substrate, each experimental point was repeated 5 times. SHGFR and CGFR are in standard cubic centimeters per minute (sccm). After printing, the printed line morphology without curing was measured immediately by using an Olympus microscope, and printed line profiles were analyzed by an image processing algorithm.

Figure 1. Illustration of the AJP principles using an ultrasonic atomizer.

2.2 Line feature extraction

As shown in Figure 2(a), the mean lines are considered as the reference lines, thus the edge roughness R_m and line overspray O_{sp} can be defined and measured to describe the printed line quality. The original image is discretized into pixels and analyzed by an image processing algorithm which developed by a MATLAB® code (MathWorks). Figure S4 in the Supporting Information describes the detailed image processing flow chart.

Figure 2. Quality analysis of line sample. (a) Definition of line morphology in printed line, (b) original line sample, (c) line detected after denoising, and (d) line detected with overspray.

To determine the mean lines, the overspray spots from the original image as shown in Figure 2(b) are removed by image preprocessing, then the mean line width is defined as^{23,27}

$$\bar{w} = \frac{1}{L} \int_0^L w(x) dx \quad (1)$$

and calculated by column of pixels from the denoised image as shown in Figure 2(c)

$$\bar{w} = \frac{1}{N} \sum_{i=1}^N w_i \quad (2)$$

where w_i is the line width of the i th column, and N is the total columns of a discretized edge.

Hence the mean edge roughness R_m is calculated by column of pixels in the discretized forms²⁷

$$R_m = \sqrt{\frac{1}{2N} \sum_{i=1}^N (\delta_{upper,i}^2 + \delta_{lower,i}^2)} \quad (3)$$

where $\delta_{upper,i}$ and $\delta_{lower,i}$ represent the deviation between actual line edge and the average line edge at each column.

After detecting the actual line edge (see Figure S5 in the Supporting Information), the original image is used for calculating the overspray of printed line as shown in Figure 2(d). Line overspray (see Figure S6 in the Supporting Information) is measured by the average distance between the printed line edges and the discrete overspray spots, and is calculated by the following discretized forms

$$O_{sp} = \frac{1}{2N} \sum_{i=1}^N (\theta_{upper,i} + \theta_{lower,i}) \quad (4)$$

where $\theta_{upper,i}$ and $\theta_{lower,i}$ represent the distance between the actual line edge and overspray spots at each column.

2.3 Space-filling based experimental design

A design space is usually explored by the traditional design of experiments (DoE) with limited level of factors. However, as the main process parameters have complicated influence on the printed line morphology, the traditional experimental design may not achieve an optimal coverage in a design space. On the other hand, as the Latin hyper sampling (LHS) is based on spacing-filling and could maximize the uniformity in a design space, it is adopted in this research to explore a design space sufficiently, and the complex correlations between different process parameters and the printed line morphology could be fully investigated. The details of applying LHS for experimental design are discussed in Supporting Information S1.^{31,32} After completing the initial experiments, additional design points may be required for further investigation. To ensure the distribution uniformity of the entire data set while adding new design points, we adopt an efficient incremental LHS approach in this research.³³

2.4 Clustering and Classification

Clustering is a common machine learning approach for identifying similar groups in a dataset. It is also called an unsupervised learning, as the original dataset is unlabeled (i.e., without

prescribed categories or priori grouping information in the data) and is clustered based on feature similarity other than driven by a specific purpose. Based on a clustering technique, an unlabeled dataset can be divided into different groups, and the data points from the same group have higher similarity than data points from different groups. In this research, to reveal the relationship of the printed line morphology in a design space, the line overspray and the mean edge roughness are set as the input features, and the distribution of printed line morphology is analyzed by a K-means clustering.³⁴⁻³⁶ The main steps to implement a K-means algorithm are discussed in Supporting Information S2.

As a classical supervised machine learning approach, a support vector machine (SVM) has been successfully applied to different classification tasks.³⁷⁻⁴⁰ The function of the SVM is to determine a statistical optimal hyperplane $f(x)$ that linearly separates the training dataset by different class labels. If the training dataset is linearly non-separable in the original feature space, the training features from original feature space would be mapped to a higher-dimensional space by a kernel function $\phi(x)$, thus the hyperplane $f(x)$ could separate the training dataset linearly in a new feature space. The identified $f(x)$ can be projected back to original feature space as the decision boundary to predict the class labels of new data points. Figure 3(a) illustrates a two-class dataset which is linearly non-separable in the original 2D space, by mapping the training features to a 3D space as shown in Figure 3(b), the dataset can be separated linearly by a hyperplane $f(x)$. In this research, as the printing quality is very sensitive to different process parameters, the SVM approach is utilized to determine a decision boundary in a design space to separate normal lines from abnormal lines, thus an operating process window can be identified to ensure the printing quality. The basic procedures of applying the SVM to identify 2D operating process window are illustrated in Supporting Information S3.

Figure 3. The basic function of SVM classification. (a) Original dataset in 2D feature space. (b) Projected dataset in 3D space.

2.5 Transfer learning

To improve the processing efficiency, there is a need to identify more operating process windows for high speed printing. Generally, an operating process window at a new print speed can be identified by a traditional machine learning approach such as the SVM. In this case, traditional machine learning methods require the newly collected training data to rebuild the model from scratch. Particularly for AJP, it is expensive to recollect sufficient labeled line samples for training, moreover, it is also a waste to discard the abundant old data set and ignore the knowledge that was learnt from the old operating process windows. Under such a circumstance, transfer learning is applied to exploit the knowledge from previous operating process windows, therefore, a new operating process window can be identified by leveraging scarce newly labeled data in conjunction with abundant old domain data.^{41, 42}

In this research, we adopt the traditional SVM to identify the operating process windows at the print speeds of 1 mm/s, 4 mm/s and 7 mm/s. Then, the relatedness between different operating

process windows is exploited by the transfer learning, and the operating process windows at new print speeds are identified respectively. In addition, to reduce the risk of negative transfer, we adopt a multiple sources transfer learning approach and compare the modeling results with single source transfer learning and the traditional SVM.^{41,43,44}

3. Results and discussion

3.1 Line quality evaluation at the print speed of 1mm/s

Figure 4. Line quality analysis at the print speed of 1mm/s. (a) Normalized line quality in the design space, (b) four clustered subspaces to present different printed line morphology, (c) a discontinuous line printed at low CGFR (Type I line), (d) a line with high roughness and high overspray printed at high SHGFR and high CGFR (Type II line), (e) a high roughness line printed at high CGFR (Type III line), and (f) a line printed with optimal morphology (Type IV line).

The initial print speed of AJP was set at 1mm/s, and the printed line morphology with respect to SHGFR and CGFR was investigated in a 2D design space. In this research, when the number of experimental points designed by LHS exceeds 160 in a design space, some adjacent experimental points become extraordinarily close and may not be distinguished due to the precision of process parameters, thus a set of 154 experimental points are adopted initially. Based on the quantified edge roughness R_m and line overspray O_{sp} , the overall printed line quality L_q can be defined as

$$L_q = w_r \times R_m + w_0 \times O_{sp} \quad (5)$$

and then normalized in the design space, the higher normalized value means better printed line quality, where w_r and w_0 represent the weights of printed line edge roughness and overspray respectively.

As shown in Figure 4(a), the overall printed line quality with respect to SHGFR and CGFR varies dramatically in different regions of the design space. To further explore the potential line morphology distribution in the entire design space, a K-means clustering approach is adopted to group the features (R_m , O_{sp}) of printed lines into four clusters, based on the clustering results, the line morphology distribution can be presented by four subspaces as shown in Figure 4(b). Subspace I presents print discontinuous lines as the low CGFR transports insufficient atomized ink. And lines can be printed with high roughness and high overspray in subspace II, because of the significant interaction induced by high SHGFR and high CGFR.

Assuming no material loss, the mass flow rate of the aerosol beam at the point of exiting the nozzle and hitting the substrate should be equal, and the corresponding continuity equation is defined as

$$\rho_e A_e v_e = \rho_l V_l \quad (6)$$

where ρ_l and ρ_e are the densities of the coalesced line on a substrate and the aerosol beam inside the nozzle, respectively. A_e is the cross-sectional area, and v_e is the velocity of an aerosol stream when exiting a nozzle. V_l is the coalesced line volume on the substrate. During the printing process, high CGFR increases v_e and A_e , hence based on eq. (6), printing at high CGFR with low print speed induces a large quantity of aerosol accumulate and builds up over a fixed width. Then the nonequilibrium liquid flow that consists of coalescing aerosol is driven by surface tension and curvature gradients until it attains its equilibrium curvature, thus spreading and high roughness is caused in subspace III.

On the contrary, as the aerosol jet works at relatively low CGFR in subspace IV, the curvature of the printed line is approaching the equilibrium state and spreading is reduced significantly. Therefore, the subspace IV can be considered as a potential operating process window to reduce line roughness and overspray. The four types of printed line morphology mentioned above are shown in Figures 4(c-f) correspondingly.

To determine an operating process window, the overall line quality L_q of printed samples in the entire design space were labeled by a threshold α and considered as a training data set, then an optimal decision boundary and operating process window were identified by the SVM. Figure 5 shows the decision boundary and the identified operating process window.

Figure 5. Identified operating process window at the print speed of 1mm/s.

The printed line quality can be further improved by increasing the threshold α and relabel the whole data set, the updated decision boundary demonstrates that for a certain AJP system (i.e. the combination of 3D printer, experimental setup and print speed), the line quality can be optimized by adjusting the SHGFR between 40 and 85 sccm, and the improved operating process window is shown in Figure 6.

Figure 6. The improved operating process window at the print speed of 1mm/s.

Despite the identified operating process windows are beneficial to optimize the printed line morphology, it is necessary to further investigate the electrical performance of different line morphology in the design space. Thus, the resistance measurements of the 154 LHS experimental points were conducted after sintering by using a two-point probe method and a Keithley 4200A parameter analyzer, then the distribution of the calculated printed line conductance in a design space is shown in Figure 7(a). Due to the inadequate material for deposition, most of the Type I lines are open circuit and the rest have very low conductance. On the contrary, as the material loss

and the voids caused by high overspray, the electrical conductance of the Type II lines remains relatively low in the design space. Despite the electrical performance of the Type III lines is better, the improved conductance is mainly caused by the inordinate increase of CGFR, which can enlarge the cross-sectional area of the Type III lines, but will induce excessive aerosol accumulation and spreading, hence the lines are printed with high nonuniformity and the resistance varied nonlinearly with length as shown in Figure 7(b). Compared with above types of lines in the design space, the Type IV lines which printed in the operating process windows are more suitable for AJP due to the optimal overall printing quality on the electrical performance and the line morphology. Despite printing at different CGFR is the main reason that affects the printed line conductance in the operating process window, it will be advantageous for different sensor design and customized line width printing. On the other hand, while comparing two class of Type IV lines at a certain CGFR, it can be seen that further reducing the line roughness and overspray inside the operating process window would be beneficial to improve the electrical conductance.

Figure 7. Characterization of the printed line properties. (a) Distribution of the printed line conductance (the reciprocal of resistance) and the printed line morphology in a design space. The normal lines printed in the improved operating process window are defined as Type IV-1 lines, the rest normal lines printed in the remaining operating process window are defined as Type IV-2 lines.

(b) Resistance of the aerosol jet printed lines as a function of line length under different line morphology, and (c) relative resistance of the aerosol jet printed lines as a function of bending cycles under different bending radii.

Additionally, to further study the mechanical flexibility of the Type IV lines, 4 experimental points were uniformly selected from the operating process window, then the aerosol jet 200 motion control system and the mechanical stage were adopted for bending tests (Supporting Information S5). The substrate with a linear array of 5 printed lines (length = 1.5 cm) was subjected to repeated 1000 bending cycles at the bending radii (r) of 6 (1.04% strain), and 12 mm (0.52% strain). As shown in Figure 7(c), after 1000 bending cycles, the overall relative resistance varied slightly for r of 12 mm, and increased to 1.4-fold for r of 6 mm. To improve the mechanical flexibility of printed lines, one possible strategy is to mix the silver nanoparticles ink with carbon nanotubes, and studies of mixture design are underway to improve the mechanical flexibility.

3.2 Identifying operating process windows at higher print speeds

To study the effect of the print speed on the printing quality, we increase the print speed to 4mm/s, and reprinted the line samples on the same 154 LHS experimental points. The preliminary analysis results demonstrate that increasing the print speed from 1 mm/s to 4 mm/s decreases the area of the potential operating process window dramatically, thus the printed line quality around the operating process window are more sensitive to the process parameters. Under such circumstances, to identify the decision boundary more accurately, additional experiments are conducted around the operating process window. The same procedures are also adopted at the print speed of 7 mm/s. Based on the proposed hybrid machine learning method, the line features (R_m, O_{sp}) and the overall line quality L_q of printed samples were analyzed, thus the distribution of

printed line morphology and the corresponding operating process window were identified as shown in Figure 8.

Figure 8. Analysis results of the printed line quality at the print speed of 4mm/s. (a) The distribution of printed line morphology in a design space. (b) Identified operating process window for AJP.

Compared with previous line morphology distribution at the print speed of 1 mm/s, subspace I was expanded because increasing print speed would induce the transported atomized ink to be insufficient even at relatively high CGFR. When the focused aerosol beam passes through the nozzle and hits a substrate, the increased print speed aggravated the interaction between aerosol stream and the substrate, which may cause the aerosol to depart from laminar flow behavior, thus subspace II can print lines with high roughness and high overspray even at relatively low SHGFR. While working at low CGFR in subspace III, despite the lines were fabricated continuous, the comparatively inadequate atomized ink would induce the aerosol to deposit unevenly at line edge and produce lines with high edge roughness. On the contrary, the relatively high CGFR in the

subspace III would induce excessive aerosol accumulation, build up and spreading, hence the lines were printed with high edge roughness. Therefore, based on the continuity equation, to print normal lines in a design space, it is critical to balance the complex interaction between gas flow rates and print speed.

When we further increased the print speed to 7 mm/s, the subspace I and the subspace II would continue to expand as discussed above, and the CGFR in subspace IV were increased to print normal lines. In addition, the decreased area of the subspace IV indicated that increasing the print speed would reduce the overall printed line quality in a design space. The distribution of printed line morphology and the identified operating process window at the print speed of 7 mm/s are shown in Figure 9.

Figure 9. Analysis of the printed line quality at the print speed of 7mm/s. (a) The distribution of printed line morphology in a design space. (b) Identified operating process window for AJP.

3.3 Rapid identification of operating process windows at specified print speeds

In present research, the labeled line samples at the print speeds of 1 mm/s, 4 mm/s and 7 mm/s are considered as source domain data. A design space at a specified new print speed is considered

as a target domain. And, the knowledge from source domain would be discovered and transferred to the target domain by an inductive transfer learning approach.^{41, 42} Based on the transferred knowledge, combine the scarce target domain line samples with abundant source domain data, the identified operating process windows at the print speeds of 2.5 mm/s and 5.5 mm/s are shown in Figure 10.

Figure 10. Operating process windows at different print speeds. Operating process window A is identified by traditional SVM at the initial print speed of 1mm/s, operating process windows B and C are identified by transfer learning from the source domain data.

To compare the modeling performance of different approaches, an operating process window at the print speed of 5.5 mm/s was identified by transfer learning and traditional SVM respectively. Scarce line samples from a target domain were printed and labeled as training data, then transfer learning exploited source data and applied the extracted knowledge to the training data for identifying an operating process window, while a traditional SVM approach was irrespective of the source data. In addition, as a weak relation between the source domain and the target domain

may induce the transfer method ineffective or negative transfer. To improve transfer performance and reduce the risk of negative transfer,⁴⁵ we adopted a MultiSourceTradaBoost algorithm to import knowledge from multiple sources, and the results were compared with single source transfer learning algorithm and the traditional SVM.^{43,44} The modeling accuracy with respect to the ratio of training data is shown in Figure 11. The results demonstrate that transfer learning with multiple sources has better performance than single source transfer learning and traditional SVM. Especially when the ratio of labeled line samples from target domain is less than 0.2, which means transfer learning approach is applicable to AJP for boost the identification efficiency and will be beneficial to identify an 3D operating process window as discussed in the following section. The detailed information of these two transfer learning algorithms are described in the Supporting Information S4.

Figure 11. Modeling comparison for identifying an operating process window at the print speed of 5.5 mm/s, error rate is evaluated by the testing data.

3.4 3D optimal operating process window

Despite identifying a 2D operating process window at a given print speed would be beneficial to optimize the printed line quality, a 3D operating process window can further illustrate the overall interaction between the three main process parameters, and would increase the design freedom for customized printing.

Figure 12. 3D LHS experimental design and print results.

In this research, the line samples that printed at given speeds were collected as initial dataset. In addition, as shown in Figure 12, 300 additional samples were generated by LHS to explore the 3D design space sufficiently, which demonstrated the overall line quality distribution of AJP in a 3D design space. The initial dataset and the additional 3D LHS dataset are considered as a training data set to model a basic classifier. A flow chart as shown in Figure 13 is proposed to further improve the modeling accuracy. If the modeling error rate is larger than a specified threshold ϵ , 30 additional experimental points will be added to the training data set by an incremental LHS for model updating, the iteration will repeat until the model converges.

Figure 13. Flow chart of identifying a 3D operating process window.

The identified separation hyperplane as shown in Figure 14 is considered as a 3D decision hyperplane to discriminate the printed line quality with respect to SHGFR, CGFR and print speed. To verify the validity of the identified 3D operating process window, the cross sections of the 3D operating process window are compared with the 2D operating process windows at the print speed of 2.5 mm/s and 5.5 mm/s. As shown in Figure 15, the cross sections are basically consistent with the corresponding 2D operating process windows, and the inconsistency is mainly caused by the difference between 2D and 3D datasets. The determined 3D operating process window demonstrates that lower SHGFR and higher CGFR will be required to print normal lines at increasing print speeds, which can be regarded as guidance for customized printing in a 3D design space.

Figure 14. An identified 3D operating process window for quality optimization and customized printing.

Figure 15. Comparison between the cross sections of 3D operating process window and the corresponding 2D operating process windows at the print speed of 2.5 mm/s and 5.5 mm/s.

3.5 Discussion

Based on the proposed hybrid machine learning method, the distribution of printed line morphology was analyzed and presented by four subspaces, and the optimal operating process windows were identified in 2D and 3D design spaces. The determined line morphology distribution demonstrated the complex relationship between the process parameters and the printed line quality. Extremely low CGFR transports insufficient atomized ink, thus the conductive lines will be printed discontinuous. On the contrary, because of the significant interaction between process parameters, high SHGFR and high CGFR will print lines with high roughness and high overspray even at low print speed. Despite reducing SHGFR avoids high overspray, the imbalance between CGFR and print speed will induce inadequate deposition or excessive spread of atomized ink, thus the lines will be fabricated with high edge roughness. To balance the interaction between different parameters, the operating process windows were identified and served as guidance for adjusting process parameters to fabricate normal lines in a design space. In addition, to boost the identification efficiency, a transfer learning approach was applied to determine an operating process window at a specified print speed, and the modeling results indicated the applicability of this approach for AJP.

4. Conclusions

In this paper, a hybrid machine learning method was proposed to determine optimal operating process windows by exploring the relationship between process parameters and printed line quality in AJP. Based on the proposed method, the printed line morphology distribution was analyzed in different design spaces, and the optimal operating process windows were identified for printed line

quality optimization. The identified operating process windows would be beneficial to balance the relationship between different process parameters, thus the lines could be fabricated with better edge definition and lower overspray in a design space.

Due to the combination of classic machine learning algorithms, including experimental sampling, data clustering, classification and knowledge transfer, the process of the printed line quality optimization is more systematic and efficient than traditional experiment-based approaches. Moreover, the proposed method is not restricted to AJP, it can be adopted as a data-driven based approach for quality optimization in other 3D printing technologies, such as inkjet printing.

In this research, SHGFR, CGFR and print speed were investigated as limited influencing factors because of the adjustability during the printing process. In the future, more factors such as ink properties, tip size, standoff distance and platen temperature will be investigated and high dimensional operating process windows will be identified for quality optimization in AJP.

ASSOCIATED CONTENT

Supporting Information

Detailed description of applying Latin hypercube sampling, K-means clustering and transfer learning; main procedures of SVM to identify an operating process window; bending test of printed lines. This material is available free of charge via the Internet at <http://pubs.acs.org>.

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Notes

The authors declare no competing financial interest.

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