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Void content reduction of composites with sensor-aided injection strategy in liquid composite molding process

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Abstract

Void is one of the critical issues affecting the mechanical performance of fiber-reinforced polymer composites. Aiming at the composite parts formed by Liquid Composite Molding, this develops a sensor-aided injection strategy, including a real-time online monitoring module and a sensor-aided injection system, which realizes continuous detection of resin flow and the automatic injection flow rate adjustment to minimize void content. Flow front profile continuously recorded by the monitoring module in resin flow direction is reconstructed in real-time. It provides a digital representation of the saturation state of the fibrous preform, which is referred to Digital Process Twin (DPT) in present work. The local flow front velocity is then extracted from the DPT, thus the sensor-aided injection system can maintain the flow front velocity at an optimal level, regardless of the cross-sectional geometry. Experimental investigation confirms the representative of DPT to actual flow. Characterization of void content by micro-computed tomography shows that the proposed sensor-aided injection strategy not only effectively decreases the void content from 0.32%, 0.34%, and 0.79% to 0.18%, 0.18%, and 0.19%, but also significantly improves the part quality consistency. Furthermore, to the best knowledge of the authors, This work is the first to use micro CT to investigate the effect of velocity on void content from the mesoscopic and microscopic scales, although the topic has been widely investigated theoretically.

1. Introduction

Liquid Composite Molding (LCM) is a family of composite manufacturing processes in which the dry fibrous preform placed in the mold cavity is impregnated with resin driven by pressure. LCM techniques, such as Vacuum Assisted Resin Infusion (VARI) and Resin Transfer Molding (RTM), is widely used in industries, for instance, wind energy, ship, aerospace [1–3] because of their advantages of low cost and suitability for forming extra thick and large-size parts in one piece. However, there are still problems in the application of LCM. Among them, defects caused by incomplete impregnation, i.e., voids and dry spots, may significantly affect the quality of products. Many researchers have established relationships between void content and mechanical properties of composites, such as shear, tensile and flexural strength, which shows that the mechanical properties decrease with the increase of porosity [4, 5]. Thus, as an important problem having direct applications in industries, it is worth to conduct an in-depth study of the fluid flow behavior in fibrous reinforcement to minimize the voids content in composites.

Void in composites made by LCM process is mainly caused by the non-uniform flow front velocity in the fiber tows and the gap between fiber tows during the impregnation of the fiber bed [6]. As shown in figure 1, these two flow fronts meet and generate microscopic voids inside the fiber bundles when the flow in the gap is faster or mesoscopic voids in the gap when the flow velocity is higher inside the bundles [7]. Regarding the fiber
preform as a single scale porous medium, Darcy’s law [8] is usually used to describe the liquid flow inside:

$$V = \frac{K}{\mu} \cdot \frac{\Delta P}{L}$$  \hspace{1cm} (1)

where $K$ is the permeability constant (m$^2$), $V$ the Darcy velocity (m·s$^{-1}$), $L$ the impregnated length of part, and $\mu$ the dynamic viscosity of the fluid (Pa·s). $P = P_{in} + P_c - P_{ff}$ is the pressure drop between the inlet and resin flow front (Pa). $P_{in}$ and $P_{ff}$ denote the pressure at inlet and flow front, $P_c$ the capillary pressure caused by the capillary pressure in fiber tows.

Flow front velocity has been widely investigated theoretically as an important parameter in LCM. According to Darcy law (see equation (1)), the flow front moves fastest at the beginning of the injection due to the enormous pressure gradient induced by pressure driven resin flow and capillary effect. And then, the flow front velocity decreases gradually as the impregnation distance increases. Note that the capillary effect may accelerate or slow down the microscopic flow of resin in fiber bundles, depending on the relative magnitude of the resin driving pressure. Thus, an optimal flow front velocity should exist and gives the minimum void content in both mesoscale and microscale, and first reported by Mahale et al. [9]. The authors identified a critical value of capillary number that below which void content increases exponentially with decreasing capillary number. To obtain the optimal injection conditions, Patel and Lee proposed a modified capillary number ($Ca^*$) through void removing [10] and wettability analysis [11], which considered the influence of liquid viscosity, flow velocity, contact angle, and surface tension of the resin on the void content of composites. It is defined as:

$$Ca^* = \frac{\mu v}{\gamma \cos \theta}$$  \hspace{1cm} (2)

where $v$ is the apparent fluid velocity (m·s$^{-1}$), $\mu$ the fluid viscosity (Pa·s), $\gamma$ the surface tension of the resin (N·m$^{-1}$), and $\theta$ the contact angle between the resin and air on fiber surface (°).

For a given fabric, void content is a logarithmic function of resin flow front velocity, as shown in figure 2 and equation (3) [12, 13].
where $V_M$ is the content of mesoscopic voids, $V_m$ the content of microscopic voids. $A$, $B$, $A'$ and $B'$ are constants. This correlates flow front velocity and capillary number explicitly and gives hints that one could minimize void content in meso- and micro-scale by impregnation velocity controlling.

Several experimental methods to identify the optimal flow front velocity are reported in scientific literature. Jean et al. [14] tested the mechanical properties of composite sheets prepared with different fibers under different injection pressure conditions. The results show that the minimal void content appears where the resin velocity is equal to the optimal value. Causse et al. [15] derived the range of optimal flow velocity through capillary rise experiments using the Lucas-Ishburn model. It shows that the derived results are close to the optimal value of front flow velocity determined by measuring the void content of the final part.

An numerical implementation of the optimal flow front velocity—modified capillary number relationship [16] for void reduction shows that the void content could be minimized effectively. The optimal resin injection velocity is obtained iteratively by calculating the capillary number at the flow front in each time step numerically. Unfortunately, no experimental validation is reported on the composite part analysed by simulation. Yutaka et al. [17] combined mold-filling simulation and multi-objective genetic optimization algorithm to account for influence factors on composite part quality, i.e., filling time, ized resin, weld line and the total amount of void. However, the fabric structure-based numerical simulation makes it difficult to promote this method in industrial applications. Another problem pointed by the authors is that it is difficult to examine all void distributions in their sample using digital microscopy, which will be tackled with micro computed tomography instead. Moreover, it is quite common in actual production to see the flow front distorted due to draping, material variability, and human aspect. An offline simulation may not reduce the content of mesoscopic and microscopic voids effectively as expected.

Many research implemented active feedback control scheme in LCM to improve composite part quality. Modi et al. [18] introduced image technique to analyze the resin flow distribution and adjusted the resin flow velocity by switching on/off the injection port. Lee et al. [19] acquired the resin flow front position by optical sensor and adjusted the injection pressure of main and auxiliary injection ports to match flow front optimal pattern obtained by numerical simulation. Kikuchi et al. [20] designed a resin front monitoring system that subsequent resin flow was sensed by monitoring the electrical characteristics of circuits where electrically conductive wires were embedded orthogonally in a nonintersecting manner within mold cavities. It was concluded that the resin flow sensing subsystem could be applied to relatively slow molding processes. These work show that online active control is promising in improving composite part quality. However, the active control system is designed to reduce dry spots only (macroscopic voids). No results on mesoscopic and microscopic voids are reported. In fact, switching on/off the injection port cannot adjust the resin flow velocity continuously. Thus it might be impossible to maintain a certain optimal flow front velocity to minimize void content. Moreover, the full scale numerical simulation can be too complicated and time-consuming to apply for complex or large components in actual production.

In summary, efforts to minimize the void content of composites has been made in previous work [18–20]. However, it is still challenging to reduce the void content of real part in production because the following difficulties:

1. Continuous flow front monitoring: In addition to video recording, most methods, such as SmartWEAVE [20], optical fibers, pressure sensors, dielectric sensors for resin flow monitoring, can only monitor the flow front point wisely and fail to extend the point data to the overall flow front profile at the time of writing. The placement of these point-by-point monitoring sensors is not only time-consuming, but also a large number of sensors may reduce the mechanical properties of composite parts. Besides, although simulation schemes for flow velocity optimization have been widely reported in the literature, their conversion to industrial applications has not been reported.

2. Difficult to observe the formation and distribution of voids in multi-scale fabrics. Unlike dry spots that one can observe with naked eyes during resin impregnation, most of voids in meso- and micro-scale can only be observed with sophisticated equipment after demolding. Therefore, previous studies generally focus on the elimination of dry spots (macro voids) by adjusting the flow front. The optimization of microscopic and mesoscopic void content, especially the experimental verification is rarely reported.

In this work, we develop a sensor-aided injection strategy to reduce the meso- and micro-scopic void and improve part consistency in composite part made by Liquid Composite Molding. It includes a real-time online monitoring module and a sensor-aided injection system, which realizes continuous detection of resin flow and the automatic injection flow rate adjustment to minimize void content. Therefore, the previously mentioned
two challenges are tackled by achieving the following two goals: (1) Continuous in-plane detection of resin flow and calculation of flow velocity; (2) Self-adjusting injection based on optimal flow velocity. Note that numerical analysis on void formation in dual-scale fabric, i.e., the fabric characterized in this work will be reported with our novel numerical scheme implemented in Open FOAM in our next paper since the present one mainly focuses on the sensor-aided injection strategy.

The paper is organized as follow: The experimental plan and flow front profile reconstruction according to continuously recorded data by the proposed monitoring module is detailed in section 2. Then the local flow front velocity extraction from the Digital Process Twin (DPT) is reported in sections 3.1 and 3.2, thus the sensor-aided injection system can maintain the flow front velocity at a optimal level to reduce voids (see section 3.3). Metallographic microscopy and micro computed tomography (micro CT) are used to analyze the void content and the results are also reported in section 3.3. This work may be possibly bridged the gap between academic research and industry implementation by provide a simple and continuous way to do online monitoring and controlling.

2. Experimental investigation

2.1. Materials

A glass fiber non-crimp fabric (NCF) of areal density 425 g m\(^{-2}\) is impregnated by vinyl resin (430LV-GT250, Jinling AOC Resins Co., Ltd.) in the experimental investigation. Related performance parameters [15, 16] and resin viscosity measured at 25 °C by rotational viscometer are shown in table 1. The capillary parameters of typical vinyl resin reported in the reference [13] are adopted in the present work.

Laboratory instruments: Arduino UNO R3 MCU of Shenzhen Mingjiada Electronics Co., Ltd.; DC pump of Nanjing Xinke Electronics Co., Ltd.; Metallurgical Microscopy, ZY-H500Cof Shenzhen Zongyuan Weiyi Technology Co., Ltd. CT, Xradia 510 Versa.

2.2. Experimental method

In this paper, a digital process twin model corresponding to the actual flow of resin is established based on the information acquired by online monitoring module, which is the key component of the online monitoring module. The local flow front velocity is extracted from the digitalized model and regulated to reach the optimal value by the self-adjusted injection system. In this section, experiments are designed to calibrate and validate the feasibility of the digital process twin model and the self-adjusted injection system, as shown in table 2.

Vacuum-Assisted Resin Infusion (VARI) is used in this work. The upper mold is a vacuum bag and the lower mold is a transparent glass plate so that the actual resin flow could be observed to validate the digital process twin model. The sensors are uniformly arranged on the bottom surface of the preform along the length direction and connected to the Arduino UNO R3 microcontroller to transmit the data to computer. The sampling frequency is set to 1 Hz to ensure continuous monitoring of the flow front.

The resin infusion experiments are all carried out in a constant temperature room at 25 °C. Before injection, the resin and curing agent is mixed according to the ratio of 100:3 by weight. Then the mixture is degassed in a vacuum deaerator for 3 min.

Table 1. Capillary performance parameters of vinyl resin.

| Properties                              | Value         |
|-----------------------------------------|---------------|
| Modified capillary number               | 0.0035        |
| Viscosity/Pa s (25 °C)                  | 0.3           |
| Contact angle/°                         | 44            |
| Surface tension of the vinyl resin/mN m\(^{-1}\) | 345           |

Table 2. Experiment configuration.

| Experimental configuration | Size of preform mm\(^{-1}\) | Number of sensors | Distance between the sensors mm\(^{-1}\) | Injection method          |
|----------------------------|----------------------------|-------------------|----------------------------------------|---------------------------|
| 1                          | 400 × 100                  | 1                 | \                                      | Constant pressure         |
| 2                          | 400 × 300                  | 5                 | 75                                     | Constant pressure         |
| 3                          | 400 × 100                  | 5                 | 20                                     | Constant pressure         |
|                            | 400 × 100                  | 5                 | 20                                     | Sensor-aided injection    |
2.2.1. Linear DC voltage sensor

The linear DC voltage sensor proposed by Prabir et al [21] is used to monitor the saturation state of the fibrous preform in the mold cavity. The sensor is composed of a pair of conductive copper wires placed parallel with a constant distance between the wires, which can measure the progression of the flow front continuously.

Experiment scheme 1 is used to calibrate the sensor. The selected linear DC voltage sensor consists of copper wires of $d = 0.1 \text{ mm}$ in diameter and the distance between copper wires is $h = 5 \text{ mm}$. The video recorder is used as well to film the progression of resin flow front.

2.2.2. Digital process twin model

Experimental configuration 2, as shown in table 2, is conducted to validate the digital process twin model. Multipoint injection scheme is used to create an irregular flow front profile to verify the reliability of the digital process twin model as shown in figure 3. The injection tube is perforated align with the sensors $1^\#$, $2^\#$, and $3^\#$, while no holes on the wall of injection tube next to sensors $4^\#$ and $5^\#$. The time difference of saturation between the top and bottom sides appears once the injection port is switched on. Thus a curved profile of flow front is created in the fibrous preform.

In the experiment, sensor monitoring is used to establish a digital process twin model to obtain the flow front, and video is used to record the actual resin flow at the same time. Finally, the digital process twin model is compared with the actual flow to analyze the reliability of the monitoring flow front. The image of the resin flow front distribution at the same time is captured in several stages. 600 pixels are extracted from the video image and the digital process twin model image in the width direction using MATLAB to obtain the flow front profile. The correlation coefficient $R^2$ is calculated through the coordinate point on the 600 coordinate points.

2.2.3. Sensor-aided injection strategy

The self-adjusted injection system is built on top of the real-time online monitoring module. The two parts together form a sensor-aided injection strategy, which provides a solution for online monitoring, injection
strategy optimization and self-adjustment of the actual manufacturing procedure. The diagram of control module is shown in figure 4. The Arduino microcontroller acquires the signal to build the digital process twin model. It is also the decision-making basis for optimal flow front velocity control by regulating the injection pressure of the injection pump.

Experiment scheme 3 is conducted to validate the reliability of the sensor-aided injection system. In the experiment, the velocity distribution of sensor-aided injection and constant pressure injection are compared. For constant pressure injection experiments only the online monitoring module is used to record the resin flow front position without feedback control.

Five samples are cut from the cured plate every 80 mm starting from 40 mm away from the injection port with a size of 20 mm × 10 mm for void content measurement, as shown in figure 5. Metallurgical microscope and micro CT are used to characterize the voids. 800#, 1200#, 1500#, 2000#, W1.0 diamond polishing paste and velvet sandpaper are used to polish to ensure that the sample has no obvious polishing traces while the image is visible.

3. Results discussion

3.1. Sensor calibration
For the linear DC voltage sensor, two wires passing through the conductive medium (resin in our research) and the Arduino microcontroller form a closed circuit, as shown in figure 6. When there is no conductive medium, the resistance $R_s$ between the wires is infinite; when the length of resin impregnation and wetting between the wires increases, $R_s$ decreases gradually. Therefore, the linear DC voltage sensor is connected in series in the circuit, and the change of resistance is obtained by measuring the voltage drop across the sensor $V_s$, which can be expressed as:

$$V_s = \frac{R_s}{R_s + R_b} V_{ex}$$  \hspace{1cm} (4)

where $R_b$ is the fixed resistors (Ω), $V_{ex}$ the constant excitation voltage (V).

According to the volume resistivity equation of resin, the resistance $R_s$ is a function of resin impregnation length $l_{wet}$ for a given distance of the gap $h$ (mm):
where \( \rho \) is the volume resistivity (\( \Omega \cdot \text{mm} \)), \( d \) the diameter of the copper wire inside the sensor (mm). The resin-saturated length \( l_{\text{wet}} \) and the voltage drop across the sensor \( V_s \) satisfy the following relationship:

\[
R_s = \frac{h \rho}{dl_{\text{wet}}}
\]  

(5)

where \( dl_{\text{wet}} \) is the change in the resin-saturated length and \( V_s \) is the voltage drop across the sensor.
It can be found that the resin-saturated length $l_{\text{wet}}$ is proportional to the reciprocal of the voltage drop across the sensor $V_s$. The sensor is calibrated by simultaneously using the sensor to monitor the voltage and the resin-impregnated length of video recording. The distance to the resin-impregnated fiber from the video at each time is plotted against the monitored voltage and fitted to obtain the monitoring relational expression of the linear DC voltage sensor, as shown in figure 7. The experimental results show that there is an accurate linear relationship between the resin-saturated length and the reciprocal of voltage drop across the sensor, and there is a good linear relationship between the resin impregnation distance and the reciprocal of the monitored voltage. The relationship between saturated length and voltage is obtained as below:

$$l_{\text{wet}} = \frac{C}{V_s} - D$$

$$C = \frac{h \rho_s V_{ex}}{dR_b}$$

$$D = \frac{h \rho_s}{dR_b}$$

(6)

The fitting correlation coefficient $R^2 = 0.9947$, so the resin-saturated length can be obtained by monitoring the voltage according to this equation.

**3.2. Verification of the digital process twin model**

In order to visualize the resin flow, a coordinate is established in the digital model with the direction of the resin flow as the Y axis and the direction of the mold width as the X axis. In the coordinate, the five groups of linear DC voltage sensors are placed at the abscissa $x_1 = 0, x_2 = 7.5, \ldots, x_5 = 30$, while the resin impregnation length monitored by each sensor is labeled as $y_1, y_2, \ldots, y_5$ with orange lines, as shown in figure 8. According to the data of different sensors at a particular time $t_{\text{mp}}$, the Lagrange interpolation method is used to construct the resin flow front profile $f_{\text{l}}(x)$ with blue curve based on these five coordinate points in the digital model.

First, the basis function is constructed. The equation $l_k(x)$ is served as a 5th-degree polynomial and satisfies the interpolation nodes $x_1, x_2, \ldots, x_5$:

$$l_k(x) = \begin{cases} 0, & i \neq k \\ 1, & i = k \end{cases}$$

(8)

The interpolation polynomial can be obtained from the interpolation basis function as follows:

$$f_{\text{l}}(x) = \sum_{k=0}^{n} y_k l_k(x) = \sum_{k=0}^{n} y_k \prod_{i=0, i \neq k}^{n} \frac{x - x_i}{x_k - x_i}$$

(9)

The flow velocity can be obtained using the area integral and arc length integral of two adjacent curve functions:

![Figure 9. Comparison of digital process twin model and actual flow front. (a) $t = 26$ s; (b) $t = 85$ s; (c) $t = 172$ s; (d) $t = 287$ s.](image-url)
Figure 9 shows the flow front position by the real-time online monitoring module (in red) in four stages. Figure 9(a) shows the stage that the resin started impregnating the preform. As expected, the flow front shows a curved profile because of the multipoint injection scheme. At this stage, the preform is not fully impregnated by resin along the width direction. The runner effect caused by the wires consisted of the sensors accelerates the flow nearby them because the system only monitored the impregnation of preform at the sensors instead of the unsaturated region without sensors. However, the flow front reconstructed from the real-time monitoring module shows good consistency with the actual flow and the correlation coefficient R^2 is 0.97. The flow front becomes a continuous curve when the preform is fully impregnated along the width direction, as shown in figures 9(b)–(d). The reconstructed flow front profile matches better with the actual flow as the increase of saturated length (R^2 = 0.99). This shows that the real-time online monitoring module could continuously and effectively monitor the resin flow front.

MATLAB script is used to calculate the relative error between the real-time monitoring module and the actual flow front. A significant relative error at t = 26 s is observed because parts of the preform are not impregnated. However, the distance between the model and the actual flow front is less than 2 mm. The relative error becomes negligible when the preform is fully saturated along the width direction. It shows the capability of the real-time monitoring module to reconstruct the actual flow while the sensor is arranged along the flow direction. Moreover, the runner effect caused by the sensor can be ignored when the flow is fully developed. Moreover, increasing the number of sensors can further improve the reconstruction accuracy of the flow front.

\[
\nu_{\text{in}} = \frac{\int_{S_{\text{in}}}^{x\text{in}} (f_{\text{in}}(x) - f_{\text{in}}(x)) \, dx}{\int_{S_{\text{in}}}^{x\text{in}} f_{\text{in}}(x) \, ds}
\]  

(10)
3.3. Analysis of flow velocity and void content

According to the modified capillary number and the related property parameters of the vinyl resin-glass fabric system, the optimal flow velocity of vinyl ester resin $v_{opt}^{imp}$ can be determined as:

$$v_{opt}^{imp} = \frac{C_a \gamma \cos \theta}{\mu} \approx 0.3 \text{ mm} \cdot \text{s}^{-1}$$

(11)

Therefore, $v_{opt}^{imp} = 0.3 \text{ mm} \cdot \text{s}^{-1}$ is used as the target of the self-adjustment in the sensor-aided injection strategy.

Figure 10 shows the actual flow front velocity obtained from the constant pressure injection and sensor-aided injection from the digital process twin model. The flow front velocity can be calculated from the difference of flow front position at two neighboring time steps $t_m$ and $t_{m+1}$. Figure 10(a) gives the flow front velocity as a function of saturated length in the constant pressure injection experiment. The flow velocity initially reached its maximum value, then it decreases as the saturated length increases. According to Darcy’s law, the pressure gradient is significant at the beginning of resin injection, thus the resin flow velocity reached the maximum. Then, the pressure gradient decreases. After the resin-saturated length reached 25 cm, the flow velocity tended to be $0.1 \text{ mm} \cdot \text{s}^{-1}$.

Figure 10(b) is the curve of the resin flow velocity in the sensor-aided injection experiment. The flow front velocity first reaches the maximum value, then decreases rapidly to the optimal flow front velocity of $0.3 \text{ mm} \cdot \text{s}^{-1}$.

Figure 11. Comparison chart of flow velocity and void content distribution.

Figure 12. Voids in samples made by constant pressure injection measured by metallographic microscope. (a) $l = 4 \text{ cm}$; (b) $l = 12 \text{ cm}$; (c) $l = 20 \text{ cm}$; (d) $l = 28 \text{ cm}$; (e) $l = 36 \text{ cm}$.

Figure 12. Comparison chart of flow velocity and void content distribution.
under the automatic feedback of system control. The sensor-aided injection strategy could regulate the flow front velocity to the optimal value even though the saturated length increases, showing the capability of sensor-aided injection strategy to control the resin flow velocity continuously and effectively.

Figure 11 shows the flow front velocity and void content as a function of resin-saturated length for both sensor-aided injection and constant pressure injection strategies. It shows that the void content is always kept at a similar level when sensor-aided injection strategy is in effect. The void content is also lower than constant pressure injection strategy, in which the void content decreases first and then increases.

Figure 12 shows the metallograph of voids in the samples cut from cured plate made by constant pressure injection. The void content decreases first and then increases as the velocity decreases. It shows that the void formation mechanism is closely related to the flow front velocity. The faster flow front velocity than $v_{opt}$ results in more microscopic voids in fiber tows, while the capillary force plays a dominant role because of the decrease of flow front velocity near the outlet. It accelerates the flow inside the fiber tow and mesoscopic voids are created in the gap. The maximum void content reaches 4.1% due to the deviation of resin flow front velocity from optimal value. The resin flow front velocity at 12 cm is 0.3106 mm·s$^{-1}$, which is close to the optimal flow front velocity of 0.3 mm·s$^{-1}$, and the void content is the minimum: 1.5% (measured by metallographic microscope).

The metallograph of voids in samples made by sensor-aided injection are shown in figure 13. The rein flow velocity next to inlet is 0.3659 mm·s$^{-1}$ ($l = 4$ cm), which is larger than the optimal value. Therefore, the void
content is 1.9%, slightly higher than other samples. However, the void content is still less than the plate made by constant pressure injection. The flow front velocity of the other four samples for the case with the sensor-aided injection strategy in effect is under the automatic feedback control, and the flow front velocity is 0.2888 mm·s$^{-1}$, 0.2916 mm·s$^{-1}$, 0.2624 mm·s$^{-1}$, and 0.2717 mm·s$^{-1}$ respectively, which is very close to the optimal value 0.3 mm·s$^{-1}$, and the void content of the corresponding positions is 1.6%, 1.4%, 1.2%, and 1.4%, respectively (measured by metallographic microscope).

The samples cut from the cured plates where $l = 12$ cm, $l = 20$ cm, $l = 28$ cm made by constant pressure injection and sensor-aided injection are also examined using micro CT. The void distribution is shown in figure 14. More large-sized voids can be found in the samples by constant pressure injection, while the size of voids is more uniform in samples made by sensor-aided injection. Furthermore, the voids generally present on the interface between the fiber bundles and the resin when the sensor-aided injection strategy is in effect.

Figure 15 gives the void content calculated from micro CT images, including the volume void content of each sample and void content calculated from each slice of the micro CT image sequence. The average void content of each sample, calculating from several observations in one sample, is also plotted in figure 15. The void content from each slice gives larger void content by constant pressure injection than sensor-aided injection which is consistent with figure 14.

Although metallographic microscopy is a low-cost method for void characterization, it can still qualitatively give the changing trend of void content. The result shows that micro CT can calculate the void content.
quantitatively and more accurately because it has the abilities of higher accuracy, larger field of view, and ability to observe inside the sample. The void content of the product by sensor-aided injection strategy has been significantly reduced compared with the constant pressure injection from the results of micro CT and metallographic microscopy, which shows that the system could minimize the void content by the sensor-aided injection strategy.

4. Conclusion

The sensor-aided injection strategy for Liquid Composite Molding proposed in this work shows capability in minimizing void content in composite parts. It is achieved by continuous in-plane detection of resin flow, flow front profile reconstruction and velocity extraction, and self-adjusting injection flow rate based on optimal flow velocity. Experimental results confirms the validity of the proposed sensor-aided injection strategy in minimization of void content, which shows that the void contents are decrease from 0.32%, 0.34%, and 0.79% to 0.18%, 0.18%, and 0.19% as given by micro CT. Thus, the proposed method appears to provide reliable capability in void reduction in dual-scale fabrics.

The findings are thus similar to what has been reported in earlier theoretical and experimental studies. However, we successfully developed the system, which bridge the gap between academic research and industry implementation by provide a simple and continuous way to do online monitoring and controlling. It is also found that the part made by sensor-aided injection strategy also shows a significantly improvement in quality consistency, which is not reported in previous scientific literature.

It is also worth to note that the characterization results of void content using metallographic microscope and micro CT both show a significant part quality improvement when the sensor-aided injection strategy is implemented. However, the randomness of sampling shows a significant impact on the metallographic microscope test since only 2D cross-sectional images can be obtained. Micro CT characterizes the voids by non-destructive imaging of the sample in 3D space, which shows higher accuracy.

On the basis of the findings in this work, the numerical investigation on void formation in dual-scale fabric, i.e., the fabric characterized in this work will be reported with our novel dual-scale numerical scheme in our next paper. It is implemented in the open-source CFD package OpenFOAM and will be used to reveal the optimal process and material parameters for void reduction.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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