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Run by Run Control of Time-pressure Dispensing for Electronics Encapsulation

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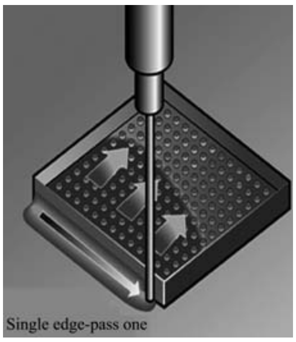
Abstract: To alleviate the influence of gas compressibility on the process performance of time-pressure dispensing for electronics encapsulation, a predictive model is developed based on power-law fluid to estimate the encapsulant amount dispensed. Based on the simple and effective model, a run by run (RbR) supervisory control scheme is delivered to compensate the variation resulting from gas volume change in the syringe. Both simulation and experiment have shown that the dispensing consistency has been greatly improved with the model-based RbR control strategy developed in this paper.

Keywords: Time-pressure dispensing, predictive model, run by run (RbR) control, electronics encapsulation.

1 Introduction

Fluid dispensing is a critical process in electronics encapsulation. For example, before reflowing or flux, the encapsulant should be pasted on the substrate by dispensing[1], as shown in Fig. 1, and in flip-chip encapsulation process, some encapsulant with high viscosity should be first dispensed on a substrate such as a printed circuit board (PCB), forming a dam or border surrounding the die and wires, and then another encapsulant with a low viscosity is dispensed to fill the inside of the dam[2] (see Fig. 2).

(a) Die encapsulation



(b) Underfill encapsulation

Fig. 1 Applications of dispensing in the electronics encapsulation

In these encapsulation processes, the consistency of the encapsulant amount dispensed is very critical, otherwise short circuit, component breaking off, or satellitic dots polluting the solder plate would happen. In order to get a good dispensing performance, one fundamental requirement is that the flow rate of the encapsulant dispensed should be controlled to be consistent over the dispensing process so that the amount of encapsulant dispensed can be accurately manipulated.

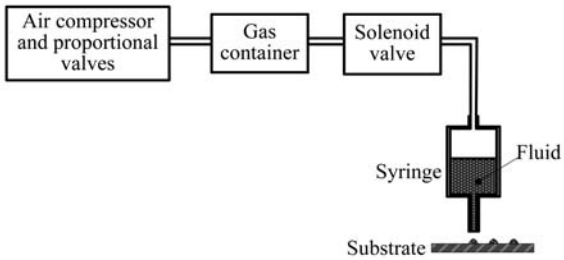


Fig. 2 Schematic of a typical time–pressure dispensing system

The time-pressure dispensing is the most widely used due to its low cost, simple operation, ease of maintenance, and flexibility for different applications[3]. Fig. 2 shows the schematic of a typical time-pressure dispensing system. When the valve is opened, the compressed air in the syringe squeezes the fluid (such as resin, adhesive, and encapsulant) out to a substrate. Unfortunately, the time-pressure dispensing process has proven to be the most difficult to model and control because the performance can be affected by many variables. One of the main variables is the air compressibility which can significantly affect the amount of fluid dispensed, especially when dispensing a minute amount with a short duration of pressure pulse (called dispensing cycle, typically less than 200 ms). Consequently, as the air volume in the syringe increases with the dispensing process proceeding, the amount of fluid dispensed can change dramatically under the action of an identical pressure pulse[3]. The inconsistency in the amount dispensed under the identical pressure pulses is considered as a serious problem in the time-pressure dispensing process[4, 5].

To resolve this problem, several models have been developed and evaluated, but most of them are numeric models[6], experiential knowledge-based models[7] and neural network models[8], which are difficult to be applied in practice. Furthermore, the adhesive used for dispensing is often epoxy which belongs to the non-Newtonian fluid[9] and difficult to model. So far, the practical research has focused on the analytical approach of modeling the dispenser as a pipe flow[10−12] by assuming the adhesive as a New-

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tonian fluid. However, the results for the Newtonian fluid usually cannot be applied to the non-Newtonian fluid[6]. On the other hand, the control of the time-pressure dispensing has been studied by using different technologies and methods, such as extra sensing technology[13], knowledge-based experience[7], and SPC method[14]. Recently, a simple model-based iterative off-line control method was proposed by regulating the air pressure[11]. It is noted that almost all the above control methods employed pressure to compensate the process variations. Practically, they are difficult to realize because the pressure may not be an efficient control variable for its compressibility and slow response.

In this research, a model-based run by run (RbR) control strategy is presented to control the dispensing process. First, a model for predicting the amount of fluid dispensed is delivered from the typical non-Newtonian power-law fluid. Finally, an RbR controller based on exponentially weighted moving average (EWMA) supervising is developed to alleviate the variation resulting from the air compress. Unlike the existing dispensing control method which employs pressure as controllable variable[10, 13], in this paper, we choose dispensing time as the control variable, which makes the control process more feasible and effective. Both simulation and real experiment have shown that the dispensing consistency has been greatly improved.

2 Predictive model development

In electronics encapsulation, the fluid amount dispensed in a cycle is very small compared with the fluid volume left in the syringe, and it is appropriate to only consider the dynamics of the fluid flowing in the needle, which can be seen as a small diameter rigid pipe as show in Fig. 3.

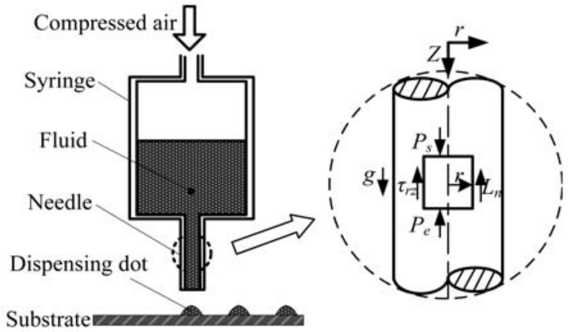

Fig. 3 Structure of the dispenser and the flow in a vertical pipe

For a fully developed pipe flow, it can be known that the pressure drop through the pipe $\Delta P^* = P_s - P_e$ and gravitational body force $\rho g z$ is balanced by the wall friction F_w which relates the wall shear stress τ_w. Then, the force balance equation is obtained for the control volume in the cylinder with length L_n:

$$2\pi R\tau_w L_n = \pi R^2\Delta P = \pi R^2(\Delta P * + \rho g L_n) \tag{1}$$

$$\tau_w = \frac{R\Delta P}{2L_n} \tag{2}$$

where τ_w and R are the shear stress at the wall and inner radius of the needle, respectively. By the same method, the inner shear stress τ is derived at the arbitrary point in the needle with radius $r < R$ as

$$\tau = \frac{r\Delta P}{2L}. \tag{3}$$

Then

$$\frac{\tau}{\tau_w} = \frac{r}{R}. \tag{4}$$

The shear rate $\dot{\gamma}$ is described as[6]

$$\dot{\gamma} = -\frac{\mathrm{d}u_z}{\mathrm{d}r} \tag{5}$$

where u_z is the flow velocity through the pipe in the radius$r$. In electronics encapsulation, the generalized power law equation is the most widely used to describe the relation between the fluid dynamic viscosity η and shear rate $\dot{\gamma}$ which is given by[15]

$$\eta(\dot{\gamma}) = k\dot{\gamma}^{N-1} \tag{6}$$

where k is the fluid apparent viscosity and N is the measurement of the rheology with $N \neq 1$, or else it will be a Newtonian fluid. Substituting (5) and (6) into (4) yields

$$-\mathrm{d}u_z = \tau_w \frac{r}{R}\frac{\mathrm{d}r}{\eta} \tag{7}$$

$$\tau = k\dot{\gamma} = k\left(-\frac{\mathrm{d}u_z}{\mathrm{d}r}\right)^N. \tag{8}$$

The boundary conditions of u_z satisfy $u_z = 0|_{r=R}$ and $u_z < \infty|_{r=0}$, thus from (8), we have

$$u_z = \frac{N}{N+1}\left(\frac{\Delta P}{2L_n k}\right)^{\frac{1}{N}}\left(R^{\frac{N+1}{N}} - r^{\frac{N+1}{N}}\right). \tag{9}$$

The flow rate through the needle is

$$Q = \int_0^R \pi r^2 u_z \mathrm{d}r = \frac{N\pi R^3}{3N+1}\left(\frac{R}{2L_n k}\right)^{\frac{1}{N}}\Delta P^{\frac{1}{N}}. \tag{10}$$

It is noted that the coefficient of ΔP is related to the structure of the syringe and the fluid dynamic. Let

$$K = \frac{N\pi R^3}{3N+1}\left(\frac{R}{2L_n k}\right)^{\frac{1}{N}}. \tag{11}$$

Equation (10) can be simplified to

$$Q = K\Delta P^{\frac{1}{N}}. \tag{12}$$

The fluid volume dispensed during cycle T_0 is

$$V = \int_0^{T_0} Q\mathrm{d}t = K\int_0^{T_0}\Delta P^{\frac{1}{N}}\mathrm{d}t. \tag{13}$$

Equation (13) is the predictive dispensing model. It can be seen that only ΔP and T_0 can be used to modulate the dispensing volume. Since ΔP can be measured, for convenience, (13) is presented as

$$V = A(t)t \tag{14}$$

where $A(t)$ is an alterable coefficient about dispensing time t. For a given t and resource pressure P_0, $\Delta P(t)$ can be measured by a pressure sensor, and parameters K and N can be identified, which will be discussed in the following section. Thus, $A(t)$ is a constant.

Equations (13) and (14) can predict the fluid amount dispensed while the air volume in the syringe dose not change severely. However, with the dispensing process proceeding, the fluid left in the syringe decreases and the air amount increases, the influence of air compressibility becomes more severe, which leads to (13) having more serious to mismatch with the real process. Since it is a slow drift process, this drift can be compensated by a proper control strategy, such as the RbR controller discussed in the next section.

3 RbR controller design

3.1 Discussions

From the control point of view, the dispensing process is an RbR batch process as shown in Fig. 4. Though the pressure response inside the syringe is very fast during each dispensing cycle, the whole dispensing is slow in terms of the dispensed volume. Two problems are discussed below:

1) Direct pressure control during the dispensing cycle is impossible due to the short dispensing cycle with $T_0 = [50\,\text{ms},\ 80\,\text{ms}]$ in the high-precision dispensing and the slow reaction of the pneumatic control system (hardware limitation). Practically, the only one possible way to control the dispensed volume is to control the pressure valve open time t_d, i.e., the rising period of the pressure curve, but T_0 is not changed once decided before real dispensing to keep a fast dispensing frequency.

2) It could be possible to design a complex control algorithm in theory, however, it is impossible to apply it in practice due to the physical limitation. First, the resolution t_d is very coarse due to the hardware limitation of the value. An elegant control action cannot show its advantages under the coarse actuation. Second, the dispensing system has to share the computation resources with other parallel units, such as vision system, $x-y$ table motion, bond head motion, etc. Only a few milliseconds are available for the dispensing computation.

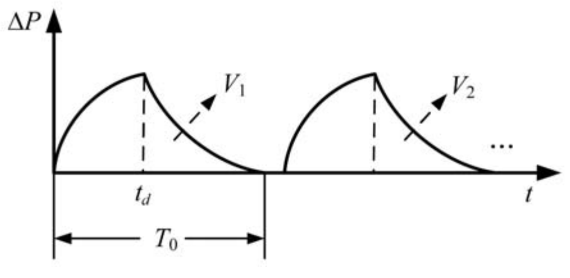

Fig. 4 Pressure variation of an RbR dispensing process

Since it is a slow process between runs, an RbR control would be suitable at this supervisory level. To alleviate the influence of system repetitiveness, the sample dispensing is required for the model calibration (parameter identification) before the real dispensing. The valve open time t_d can be easily and correctly determined at the beginning of the dispensing, and only needs to be fine-tuned when the fluid amount left in the syringe gradually changes.

3.2 RbR controller design

The most widely used RbR controller is based on an EWMA scheme[16]. The EWMA control assumes a linear process input-output relationship, and also assumes that there exists slow drift or persistent change in the model intercept part. It then achieves an estimation of process state, and the recipe changes necessarily to keep the process on target.

Because modulating dispensing pressure is not practical, the pressure from the compressor is always fixed (but its response in the syringe is dynamic). Considering the disturbance resulting from the tailing effect, the inconsistent distance between the needle and the substrate. An RbR dispensing controller is developed as shown in Fig. 5, in which P_0 is the pressure of gas resource. For convenience, we assume that the fluid amount dispensed in the n-th cycle is as

$$V(n) = \alpha A(t(n))t(n) + \nu(n) \tag{15}$$

where $t(n)$ and $\nu(n)$ are the valve opening time and disturbance of n-th cycle, respectively, α is the gain between the controller input t and the measured output V[17]. It is assumed that the disturbance can be modeled as integrated moving average, IMA (1, 1), time series of the form

$$\nu(n) - \nu(n-1) = \varepsilon(n) - \theta\varepsilon(n-1) \tag{16}$$

where ε is uncorrelated noise with variance, θ is a weighted coefficient. The function of the EWMA filter is to estimate the disturbance from the process data. The minimum mean-squared error (MMSE) one-step-ahead estimate of an IMA (1, 1) process is[18]

$$\hat{\nu}(n+1) = \theta\hat{\nu}(n) + (1-\theta)\varepsilon(n). \tag{17}$$

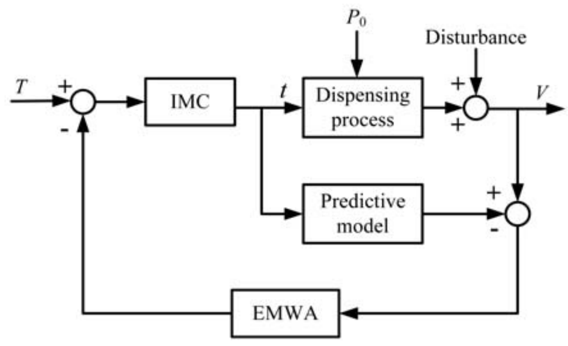

Fig. 5 RbR control process

The result in (17) shows that the MMSE estimate for the disturbance is a weighted average of the current measured disturbance and the previous estimate of the disturbance. In practice, the value of θ is unknown. Thus, a tuning parameter ω is chosen to govern how quickly the dispensing process data are discounted. When ω is chosen to be close to one, the estimate of ν is updated very slowly, and when ω is zero, only the most recent measurement is considered when estimating ν. It follows that the updating expression for the disturbance estimate is analogous to (17):

$$\hat{\nu}(n+1) = \omega\hat{\nu}(n) + (1-\omega)\left(V(n) - \beta t(n)\right) \tag{18}$$

where β is the estimate of the dispensing process gain which is assumed for the moment to be equivalent to the actual process gain α.

After the EWMA filter estimates the dispensing process offset, the recipe of the following run is determined through a simple model inversion:

$$t(n+1) = \frac{V_d - \hat{\nu}(n+1)}{\beta} \tag{19}$$

where V_d is the desired fluid amount dispensed.

4 Simulation and experiment

4.1 Model validation

To consider the disturbance from the non-Newtonian fluid variation, before real dispensing, parameters K and N of (13) have to be identified at a pair of fluid heights, which is called "operating conditions" in this paper. In the syringe, for gas volume which is slowly increasing during dispensing, it is apparent that the parameters identified at the selected operating condition may not fit the other fluid levels very well. Thus, a proper choice of the operating condition will be critical to the parameter estimation. To decide the operating conditions, choosing some typical pairs of syringe fluid heights, such as (100%, 90%), (100%, 80%), (80%, 90%), etc. to numerically simulate by using the software Fluent 6.2, the overall performance of (13) can be compared in terms of the mean of the approximation errors which achieves at all different fluid heights as shown in Fig. 6. This sensitivity analysis demonstrates that if both of the fluid heights are between 40% and 100% level, the identified model will have the minimum mean error on all the other fluid levels. For convenience, we can easily choose one height as the full level and the other one as 50% level for model identification. The result is shown in Table 1, in which K and N are identified by the Newton iteration method, and V_N and V_M are the numerical volume and the predicted volume of the model, respectively.

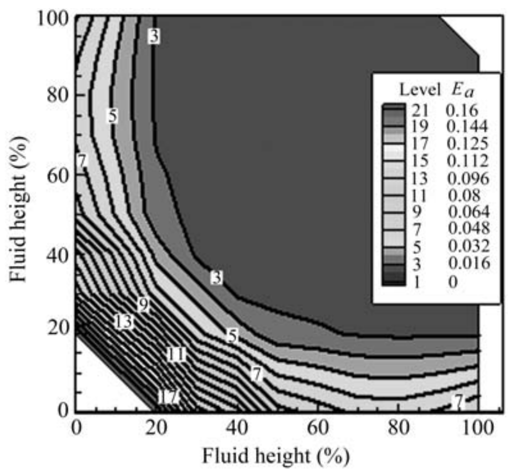

Fig. 6 Averaged error (E_a) map of dispensed volume

Table 1 Volume comparison come for (13) (parameters from two levels, 50% and 100%), $N = 0.49596$, $K = 8.2771436$ E-7

Level (%)	V_N (mm^3)	V_M (mm^3)	ε(%)
100	0.2092	0.2092	0.0018
90	0.1820	0.1818	0.080
80	0.1655	0.1656	0.10
70	0.1513	0.1513	0.029
60	0.1401	0.1402	0.057
50	0.1373	0.1373	0.0018
40	0.1262	0.1262	0.059
30	0.1243	0.1244	0.10
20	0.1191	0.1180	0.95

From Table 1, it can be seen that the predictive model has an excellent precision, but the error increases with the decreasing fluid level because the air compressibility becomes more severe.

4.2 RbR control

The predictive model and RbR controller derived in the previous sections are validated in this part by experiments. The experiment system includes an air supply controller provided by ASM Assembly Automation Ltd. HK, a command valve provided by SMC, and a transmission line with the internal diameter of 4 mm and length of 3.2 m. In order to get the instantaneous ΔP, a pressure transducer is connected to the line near the syringe chamber to sample its pressure with interval $\Delta t = 0.2$ ms (here we consider the value of ρgz according to (1)). To reduce the random error, the total amount of the fluid dispensed in ten cycles is measured by a vision system[4], and then the average is taken to represent the fluid amount dispensed of one cycle. Furthermore, silicon oil is selected as the dispensing material to reduce the error due to the time dependence associated with non-Newtonian fluids.

After calibrating the parameters of (13), the RbR control strategy is employed and used to compare with the proportional-integral (PI) controller, which is one of the most common controller in industry practice. The result is shown in Table 2. From Table 2, it can be seen that the dispensing performance is obviously improved compared with the PI controller and the open loop dispensing.

To measure the degree of the improvement, the standard deviation$\sigma$and variation var are used, which are given by

$$\sigma = \sqrt{\frac{\left(\sum\limits_{i=1}^{m}(V_i - \bar{V})^2\right)}{m}} \tag{20}$$

and

$$var = \frac{(\max\{V_i\} - \min\{V_i\})}{\bar{V}} \tag{21}$$

where $i = 1, 2, 3, \cdots, m$, $\bar{V}$ is the mean of the sample V_j and m is the sample number ($m = 10$ in this paper, i.e., ten fluid levels). From (20) and (21), we can find that standard deviation is the consistency degree of the total samplesand the variation gives prominence to the maximal wave, which is an important index to evaluate dispensing quality. The result is shown in Table 3. It can be seen that the mean of the actual dispensing amounts with the control strategy delivered in this paper is closely approaching to the desired amounts. The slight difference likely results from the experimental uncertainties, including the measurement noise, the limited resolution of t_d, etc. It is also observed that the deviation is significantly reduced from 0.25% to 0.064% and the maximal deviation from 23.4% to 5.59%. The results show that the RbR controller can improve the dispensing consistency effectively.

Table 2 Control results with different control strategies

Measured dot amount (mg)	Desired dot amount (mg)	Measured dot amount (mg)		
		Without control	PI control	EWMA control
10	0.036	0.0356	0.0358	0.0358
9		0.0348	0.0366	0.0358
8		0.0336	0.0352	0.0364
7		0.0324	0.0356	0.0356
6		0.032	0.0368	0.0358
5		0.0308	0.0352	0.036
4		0.0302	0.0346	0.0356
3		0.03	0.0342	0.0348
2		0.0288	0.0336	0.0362
1		0.0282	0.0334	0.0356

Table 3 Mean, standard deviations and variations of the measured fluid amount dispensed with different control strategies

	Desired dot amount (mg)	$\bar{V}$ (mg)	σ (%)	var (%)
Without control	0.036	0.0316	0.25	23.4
PI control		0.0351	0.11	9.687
EWMA control		0.0358	0.064	5.59

5 Conclusions

A simple model is developed for the fluid amount dispensed estimation. After properly selecting parameters, the models can very well estimate the fluid amount at all fluid levels. With the properly identified parameters, the influence of the air compressity can be well compensated via an RbR supervisory control scheme. Both simulation and experiment show that the better performance is achieved by using the proposed RbR dispensing control.

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