Statistical Approach for Cycle Time Estimation in Semiconductor Packaging Factories

W. L. Pearn, Yu-Ting Tai, and J. H. Lee

***Abstract*—In the semiconductor industry, to enhance customer satisfactions and ability of quick responses, the development of cycle time estimation model is very important. Cycle time estimation is an essential planning basis, which has many applications, especially on the analyses of performance indexes, capacity planning, and the assignments of due dates. In this paper, we provide a statistical approach for cycle time estimation in semiconductor plastic ball grid array (PBGA) packaging factories. Due to today's fierce competitive environments in the semiconductor industry, planners involved in PBGA packaging factories need an approach to obtain estimated cycle times with different confidence to ensure the due date assignments more accurately. Therefore, upper confidence bounds of estimated cycle times at various confidence coefficients are also presented in this paper. We demonstrate the applicability of the proposed cycle time estimation model incorporating the upper confidence bounds by presenting a real-world example taken from a PBGA packaging shop floor in a semiconductor packaging factory located in the Science-Based Industrial Park in Hsinchu, Taiwan.**

***Index Terms*—Cycle time estimation, Gamma distribution, plastic ball grid array.**

I. Introduction

To increase the customer satisfaction in demand and enhance the ability of quick response, semiconductor manufacturers need to develop a model in order to estimate cycle times fast and accurately. Cycle time estimation is an essential planning basis, which has many applications, especially on the analyses of performance indexes, capacity planning, and the assignments of due dates in the semiconductor industry. Semiconductor manufacturing process is comprised of four major processing stages involving wafer fabrication, wafer probing process, integrated circuit (IC) packaging, and final test process. Wafer fabrication and wafer probing processes are usually referred to as the "front-end," while IC packaging and final test processes are referred to as the "back-end" of production. In this paper, we present a statistical model for cycle time estimation in a plastic ball grid array (PBGA) packaging factory at the IC packaging processing stage in order to assist the proper assignment of due dates and to enhance the ability of quick responses in the whole semiconductor manufacturing process.

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In this paper, we focus on constructing a model to be used for cycle time estimation in a plastic ball grid array (PBGA) packaging factory. The PBGA packaging processes are increasingly popular because of their efficient mounting real estate, good thermal, and electrical performance [1]. PBGA has emerged as a popular array packaging method since it can include higher input/output (I/O) counts on limited board area than the conventional peripheral lead frame packages, such as plastic quad flat packages (PQFPs). The PBGA packaging processes have been applied in extensive applications such as cellular phones, which require high I/O counts on reduced board. Generally, the process of PBGA packaging involves ten major operations: 1) the grinding of the wafer back; 2) the mount of wafer; 3) the sawing of wafer; 4) the bonding of die; 5) the bonding of wire; 6) the molding; 7) the marking; 8) the mounting of ball; 9) the singulation; and 10) the inspection, as shown in Fig. 1. In the process, dies are mounted and bonded by gold wires on substrate strips. A substrate strip usually comprises four or eight devices depicted in Fig. 2. In molding operation, dies are encapsulated as PBGA packages. Unlike leadframe packages, PBGA uses solder balls as the interconnect path from the package to the printed circuit boards. Solder balls are attached to the substrate by applying a flux and reflowing the solder. Finally, the individual PBGA devices are cut from the substrate strips in the singulation operation and they are placed in trays for subsequent inspections.

Cycle time estimation is an essential problem for PBGA packaging factories. In PBGA packaging factories, due to wide applications of PBGA packaging, there is a great proliferation of product types. It should be noted that the number of solder balls is a major characteristic among these various product types. Fig. 3 presents the bottom view and side view of an 8×8 PBGA packaging product. In the PBGA packaging shop floor, a job involves two cassettes comprising 20 substrate strips each, which are clustered according to their product types and processed on identical parallel machines. The job processing time may vary, depending on the product type of the job processed on. Furthermore, to prevent the critical resources from starvation (idle), the CONWIP (constant work in process) control policy is applied in order to maintain the level of WIP constant. In addition, the processing statuses of machines, such as processing, idle, or breakdown, mainly affect the cycle time at each processing operation. Due to the lack of the fast and accuracy cycle time estimation methods in PBGA packaging factories, practitioners often use constant cycle times as bases for due date assignment and scheduling. However, constant

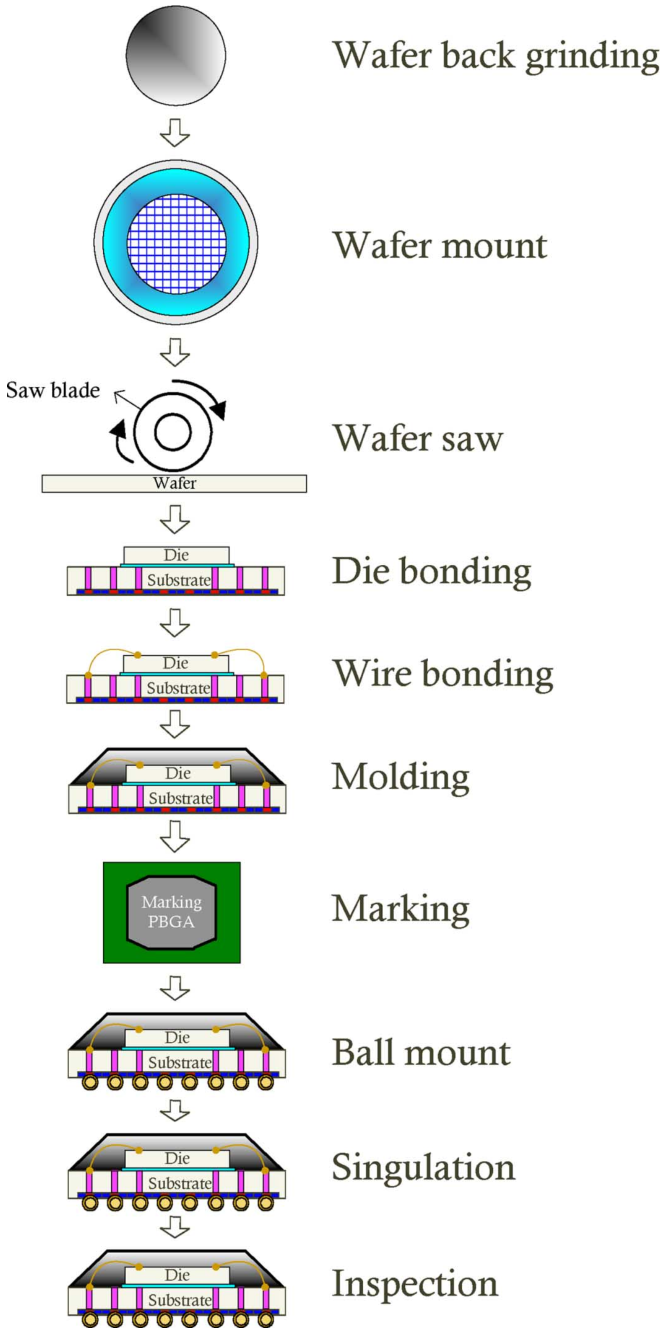

Fig. 1. PBGA packaging process flow.

Fig. 2. Substrate strip is comprised of four PBGA devices.

cycle time is so simplified that inappropriate due dates and schedules may be assigned and constructed. Therefore, the development of a model for cycle time estimation in PBGA packaging factories is difficult but essential.

In this paper, the distribution of cycle time for single operation is first formulated. A two-parameter Gamma analysis characterized with different waiting time distributions is used for the

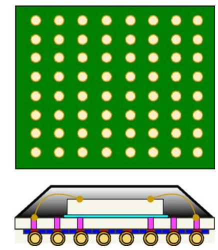

Fig. 3. Example of a PBGA packaging product via bottom and side view images.

cycle time estimation. Subsequently, the combined distribution adopting the reproductive property of the Gamma distribution for multiple operations is also presented. To demonstrate the applicability of the cycle time estimation model with the combined distribution, we consider a real-world example taken from a plastic ball grid array factory located in the Science-Based Industrial Park in Hsinchu, Taiwan. The statistical cycle time estimation model can allow us to obtain the upper confidence bounds of cycle time efficiently and further to quickly respond to customer requirements with different levels of customer service.

This paper is organized as follows. Section II presents a comprehensive review of conventional cycle time estimation literature. Section III presents the cycle time distribution for single operation. Section IV shows the combined distribution for multiple operations, and Section V gives a real-world example to demonstrate the applicability of cycle time estimation model in a PBGA packaging factory. Finally, Section VI provides the conclusions.

II. Conventional Methods for Cycle Time Estimation

In recent years, much research has focused on providing solutions to cycle time estimation. Chung and Huang [2] and Backus *et al.* [3] provided extensive discussions regarding the methods of cycle time estimation. Chung and Huang [2] classified the methods for cycle time estimation into analytical, simulation, statistical analysis, and hybrid methods. Moreover, Chang and Liao [4] considered that the tools in soft computing are also widely applied in this field.

For analytical methods, there have been many researchers who have investigated the cycle time estimation problems. Chung and Huang [2] provided an analytical approach to estimate cycle times for wafer fab with engineering lots. Shanthikumar *et al.* [5] presented a survey regarding the queueing theory for a semiconductor manufacturing system. They provided a novel solution by incorporating a key characteristic involving the dependent relationships in the classical queueing theory and expected to point out new directions in queueing model for semiconductor manufacturing systems. Morrison and Martin [6] conducted a comprehensive review regarding the queueing theory applied in cycle time estimation. They provided some practical extensions to cycle time approximations for the $\mathrm{G}/\mathrm{G}/m$-queue [6]. They also provided bounds for comparison for with mean cycle time prediction. Moreover, Huang *et al.* [7] applied analytic approximations for semiconductor wafer fabrication. De Ron and Rooda [8] described a lumped parameter model for manufacturing lines. They used the Kingman's equation and considered the basic characteristics of real lines. However, most of those works only focused on one operation, their computational results cannot be extended to whole factory cycle times. Although the methods applied queueing theory are fast in computing time, the accuracy of classical queueing models is less satisfactory than that of simulation, partly because the complex operational behaviors of semiconductor fabs cannot be represented by one single queueing model.

In recent years considerable concern has arisen over the simulation methods in cycle time estimation research. Vig and Dooley [9] proposed two methods for flow-time estimation methods. They evaluated relationships between several shop factors and effects on the due-date performance using a simulation tool. Vig and Dooley [10] further proposed a flow-time estimation and presented a regression-based approach for setting job-shop due dates. Raghu and Rajendran [11] applied a simulation method to select the best rule for shop floor dispatching and developed a due-date assignment policy for a real-life job shop. Chang [12] developed a cycle time estimation approach to provide real-time estimates of the queueing times for the jobs which still wait to perform the remaining operations. He also incorporated this estimated queueing time as essential information to the dispatching heuristics to improve their scheduling performance. However, Backus *et al.* [3], De Ron and Rooda [8], and Shanthikumar *et al.* [5] indicated that the most common solution for estimating cycle time in complex processes is simulation; however, the simulation method is time consuming and impractical for complicated manufacturing factories, especially in semiconductor manufacturing systems. In addition, Morrison and Martin [6] indicated that the method of simulation cannot offer closed-form expressions for system metrics. Simulation is used for increasing the understanding of behavior of manufacturing systems. Thus, it is difficult to apply in the realistic shop floor because it needs heavy computation loading.

For statistical analysis methods, Raddon and Grigsby [13] presented a regression model to obtain cycle times. Backus *et al.* [3] applied another statistical method, the data-mining approach, and provided nonlinear predictor variables to estimate factory cycle time. Pearn *et al.* [14] presented a due-date assignment model for the semiconductor wafer fabrication under a demand variant environment. They applied the contamination model to tackle the effect of that product mix varies periodically. Backus *et al.* [3] pointed out that the statistical models can be updated as necessary due to the ability regarding quickly reanalyzing the statistical data. Moreover, in recent years the technologies of soft computing including genetic algorithm, fuzzy, and neural network approaches are applied to estimate cycle times in semiconductor manufacturing processes. Hsu *et al.* [15] applied constraint-based genetic algorithm (CBGA) to conduct the flow time estimation model. The CBGA integrates constraint-based reasoning with genetic algorithm to reveal the rule sets. A filtering mechanism is incorporated in the CBGA to enhance computational efficiency before generating and evaluating chromosomes. Chang and Liao [4] presented a flow-time prediction method, which incorporates fuzzy rule bases with the aid of a self-organizing map (SOM) and genetic algorithm (GA). In addition, Chen [16], [17] applied hybrid fuzzy c-mean and fuzzy back propagation network approaches to estimate cycle time in semiconductor manufacturing processes.

In addition, some research works investigate the hybrid methods to estimate cycle time. Kaplan and Unal [18] combine the simulation and statistical analysis approaches to estimate cycle time. Liao and Wang [19] estimated delivery time using the hybrid method incorporating neural networks and analytical methods. Moreover, Chen [20] presented an intelligent mechanism which applies hybrid self-organization map and back propagation network in the first part and incorporates a set of fuzzy inference rules to evaluate the achievability of related output time forecast in the second part.

III. Cycle Time Distribution for Single Operation

In this paper, a statistical approach for the cycle time estimation in PBGA packaging process flow is presented. We consider a more general and more flexible statistical version of a cycle time estimation model for the PBGA packaging industries. Conventionally, the exponential distribution is commonly used for queuing-time-estimated models; however, unsatisfactory results limited their applications in practical factories. On the contrary, Gamma distribution can provide a great flexibility and cover extensive applications due to its two essential parameters. Due to Gamma distribution being nonnegative domain and right skewed probability distribution, it is used as the probability model for the estimation of waiting time. For instance, it is used for due date assignment for wafer fabrication [14]. Therefore, a Gamma distribution for the cycle time estimation at single operation has been applied in this investigation.

A. Gamma Distribution

The Gamma distribution is denoted as $\mathrm{Gamma}(\eta, \beta)$ with shape parameter η and scale parameter β. A random variable is said to have a Gamma distribution with parameters (η, β), $\eta > 0$, $\beta > 0$, if its density function is given by

$$f(x) = \begin{cases} \frac{e^{-x/\beta} x^{\eta-1}}{\beta^{\eta}\Gamma(\eta)} & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (1)$$

where $\Gamma(\eta) = \int_0^\infty e^{-y} y^{\eta-1} dy$ is known as Gamma function. The mean and variance are given, respectively, by $\mu = E(X) = \eta\beta$ and $\sigma^2 = V(X) = \eta\beta^2$. Gamma distribution is a nonnegative domain and right skewed distribution. The skewness and kurtosis (which are defined as the third and fourth moments of the standardized distribution, respectively) of $\mathrm{Gamma}(\eta, \beta)$ are $2/\sqrt{\eta}$ and $6/\eta + 3$, respectively. The skewness coefficient and the kurtosis coefficient are calculated only by using the shape parameter η. This means that the scale parameter β cannot affect the values of skewness and kurtosis of Gamma distributions. Therefore, we fix β in this investigation for the Gamma distributions. Fig. 4 presents several Gamma distributions with different combinations of η and β. As can be seen in Fig. 4, the Gamma distribution covers a wide class of non-normal applications.

Fig. 4(a)-(c) present graphs of the $\mathrm{Gamma}(\eta, 1)$ density for a variety of values of η. It should be noted that as η becomes large, the density starts to resemble the normal density [21]. To obtain the maximum likelihood estimators (MLE) of η and β for the Gamma distribution, we need to solve the following equations simultaneously:

$$\frac{-n}{\Gamma(\eta)}\frac{\partial\Gamma(\eta)}{\partial\eta} - n\log\beta + \log\left[\prod_{i=1}^{n} x_i\right] = 0 \quad (2)$$

$$-n\eta\beta + \sum_{i=1}^{n} x_i = 0. \quad (3)$$

Solving the above equation for η is rather complicated and there is no explicit close form for the maximum likelihood estimators of η. In this paper, therefore, we consider the method of moment estimators to estimate the unknown parameters η and β. The first two population moments (m_1 and m_2) of the Gamma distribution with parameters η and β are

$$m_1 = \mu = \eta\beta \quad (4)$$

$$m_2 = \mu^2 + \sigma^2 = (\eta\beta)^2 + \eta\beta^2. \quad (5)$$

By equating the first two sample moments (m'_1 and m'_2) to the corresponding first two population moments, therefore, we can obtain

$$m_1 = \eta\beta = m'_1 = \overline{x}, \quad (6)$$

$$m_2 = (\eta\beta)^2 + \eta\beta^2 = m'_2 = \frac{1}{n}\sum_{i=1}^{n} x_i^2. \quad (7)$$

From these corresponding sample moments, $\hat{\eta} = \overline{x}^2/s^2$ and $\hat{\beta} = s^2/\overline{x}$ are also obtained, where the sample average $\overline{x} = \sum_{i=1}^{n} x_i/n$ and the sample variance $s^2 = \sum_{i=1}^{n}(x_i - \overline{x})^2/n$ are the estimators of μ and σ^2, respectively.

B. Cycle Time Estimation

Like manufacturing processes in other industries, cycle time at single operation in the PBGA packaging process flow equals the process time plus the mean of waiting time. The formula can be expressed as follows:

$$CT_i = PT_i + \overline{X}_{WT_i} \quad (8)$$

where CT_i is the cycle time of operation i, PT_i is process time of operation i, and $\overline{X}_{WT_i} = \hat{\eta}_i\hat{\beta}_i$ is the mean of the fitted Gamma distribution of waiting time of operation i in the PBGA packaging process flow.

Consider a small-scaled example for cycle time estimation at single operation in PBGA packaging process flow. The example involves three parallel machines and two different product types, namely, A and B. The various processing times and estimated values regarding the two parameters of waiting time distributions for the two product types are shown in Table I. The process time is not affected by the machine processing it, but is dependent on job's product type. The "minute" is used as the unit for process time and waiting time.

TABLE I
PROCESS TIMES AND ESTIMATED PARAMETERS OF WAITING TIME DISTRIBUTIONS

Product	PT	$\hat{\eta}_1$	$\hat{\beta}_1$
A	40	21	2.5
B	56	28	3.2

Since the waiting time of product type A at this single operation is fitted as Gamma distribution with parameters (21, 2.5), the mean waiting time is 52.5 min. Similarly, since the waiting time of product type B at this operation is fitted as Gamma distribution with parameters (28, 3.2), the mean waiting time is 89.6 min. Therefore, based on (8), the estimated cycle time for product type A is 92.5 min. Similarly, 145.6 min is the value of estimated cycle time of product type B in this operation.

IV. COMBINED DISTRIBUTION FOR MULTIPLE OPERATIONS

In this section, a combined cycle time of the multiple operations in the whole PBGA packaging process flow is developed. Due to today's fierce competitive environments in the semiconductor industry, planner involved in PBGA packaging factories should be capable of providing the estimated cycle times with different confidence to ensure the due date assignments more accurately. Therefore, upper confidence bounds of the estimated cycle times at various confidence coefficients are presented.

A. Combined Gamma Distribution

To estimate cycle times of the multiple operations in the whole PBGA packaging process flow, an essential statistical property, reproductive property, of the Gamma distribution is applied; therefore, a combined distribution is applied and a combined cycle time estimated model is then constructed. Gamma distribution has a reproductive property [22]: if $x_1, x_2, \ldots, x_n$ are independent random variables each having a Gamma distribution of form

$$f(x) = \frac{e^{-x/\beta}x^{\eta-1}}{\beta^{\eta}\Gamma(\eta)}, \quad x \geq 0 \quad (9)$$

with possibly different values $\eta_1, \eta_2, \ldots, \eta_n$ of η, but with common values of β, then $x_1 + x_2 + \cdots + x_n$ also has a distribution of this form, with $\eta = \eta_1 + \eta_2 + \cdots + \eta_n$, and with the same values of β. Applying this property, let $x_1, x_2, \ldots, x_n$ be a sequence of independent distribution of $\text{Gamma}(\eta, \beta)$ and then the distribution of $x_1 + x_2 + \cdots + x_n$ is $\text{Gamma}(\sum_{i=1}^{n}\eta_i, \beta)$. Fig. 5(a)-(c) presents several Gamma distributions with different values of η and the same value of β. Fig. 5(d) further depicts the combined Gamma distribution regarding Fig. 5(a)-(c).

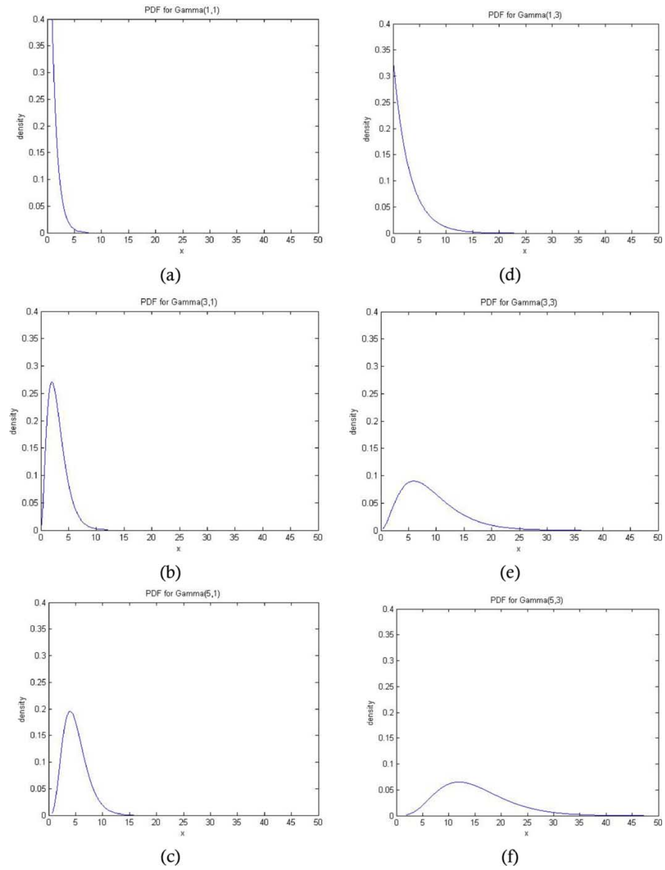

Fig. 4. Probability density functions for Gamma distribution with different parameter combinations. (a) Gamma(1,1). (b) Gamma(3,1). (c) Gamma(5,1). (d) Gamma(1,3). (e) Gamma(3,3). (b) Gamma(5,3).

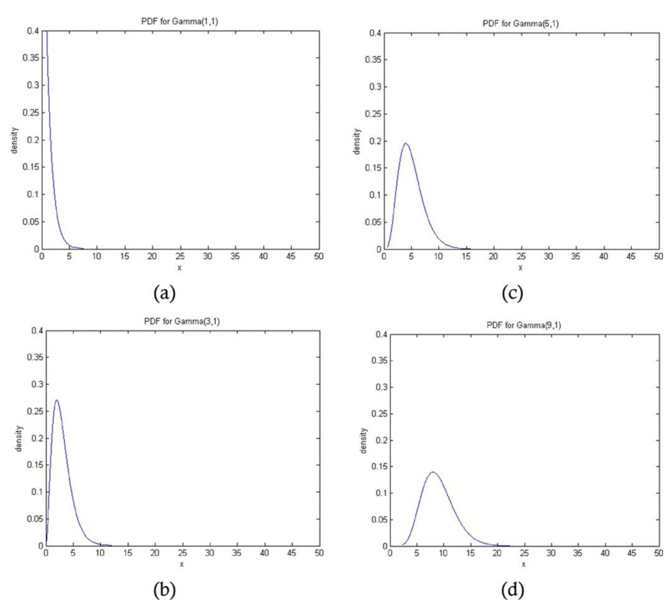

Fig. 5. Probability density functions for Gamma distribution with different η parameter combinations. (a) Gamma(1,1). (b) Gamma(3,1). (c) Gamma(5,1). (d) Gamma(9,1).

B. Combined Cycle Time Estimation

Using the reproductive property of Gamma distribution, the combined waiting time (CWT) is $\mathrm{Gamma}(\sum_{i=1}^{k}\eta_i, \beta)$. Therefore, the combined cycle time (CCT) of the whole PBGA packaging process flow can be calculated as

$$CCT = \sum_{i=1}^{k} PT_i + \overline{X}_{CWT} \tag{10}$$

where k is the total number of operations in PBGA packaging process flow, $\sum_{i=1}^{k} PT_i$ is sum of processing times for each operation, and $\overline{X}_{CWT} = \sum_{i=1}^{k} \hat{\eta}_i \times \hat{\beta}$ is the mean of the combined Gamma distribution of waiting time.

C. Upper Confidence Bounds for CCT

For an individual job, we can obtain the upper bound of the combined cycle time by taking the integral over the Gamma distribution. Using this method, cycle time equals to its process time plus δ-percentile waiting time of the combined Gamma distribution. The δ-percentile waiting time can be obtained by taking the inverse of the cumulative function of the Gamma distribution. However, in many factories, the combined cycle times of the whole PBGA packaging process flow are calculated as $CCT = \sum_{i=1}^{k} PT + \overline{X}_{CWT}$ where the mean of the combined waiting time is incorporated.

To obtain the upper confidence bounds of the combined cycle times under Gamma distribution, it requires the distribution of $\overline{X}_{CWT}$ which is a scaled Gamma. Finding exact confidence interval of μ directly from the scaled Gamma is rather difficult since the distribution of $\left(\overline{X}_{CWT} - \mu\right)$ involves unknown parameters η and β which have to be estimated. The resulting distribution becomes rather complicated. If we apply the Central Limit Theorem, then $\left(\overline{X}_{CWT} - \mu\right)/\sqrt{S_{CWT}^2/n}$ is approximately distributed as the standard normal distribution, $N(0,1)$. Consequently, we have

$$P\left(\mu \le \overline{X}_{CWT} + z_\alpha \sqrt{\frac{S_{CWT}^2}{n}}\right) \approx 1 - \alpha. \tag{11}$$

So the probability that the random upper limit as

$$\overline{X}_{CWT} + z_\alpha \sqrt{\frac{S_{CWT}^2}{n}} \tag{12}$$

is an approximate $100(1-\alpha)\%$ one-sided confidence interval for the combined waiting time. That is, $\overline{X}_{CWT} + z_\alpha \sqrt{S_{CWT}^2/n}$ provides an upper confidence bound for the combined waiting time with confidence coefficient $1-\alpha$. Since the CCT of whole PBGA packaging process flow being equal to the total process times plus the confidence interval of the combined waiting time, the $100(1-\alpha)\%$ upper confidence bound of CCT can be expressed as

$$\sum_{i=1}^{k} PT_i + \overline{X}_{CWT} + z_\alpha \sqrt{\frac{S_{CWT}^2}{n}}. \tag{13}$$

TABLE II
200 OBSERVATIONS OF WAITING TIMES

924.12	846.27	841.06	1006.39	822.11	862.54	905.38	916.17	880.57	851.42
875.02	823.61	917.66	800.92	964.78	932.20	730.45	861.04	822.38	896.09
894.14	974.60	855.93	995.49	833.86	883.29	934.68	845.15	877.89	829.25
867.32	856.49	813.87	933.68	923.56	869.71	841.99	807.58	869.08	1074.56
812.77	904.98	810.28	855.13	867.09	788.38	909.83	820.06	735.69	884.72
931.28	950.14	827.43	817.99	950.26	819.28	922.40	861.82	831.08	923.26
888.86	829.75	902.57	837.66	823.83	945.26	818.45	814.31	857.23	813.48
860.48	852.29	772.00	961.52	837.83	895.59	863.23	903.15	862.94	884.51
962.63	819.31	860.15	915.84	820.65	825.22	833.00	874.21	813.81	999.44
880.92	880.40	953.32	892.11	779.23	791.80	878.22	853.52	775.80	836.09
822.22	983.94	822.67	824.41	812.13	798.23	904.56	997.95	955.68	885.50
806.99	799.01	829.59	830.96	848.42	782.54	882.49	950.07	875.52	841.38
893.40	800.63	912.44	992.55	802.87	858.84	848.29	855.55	776.71	938.88
848.86	984.85	901.08	896.28	890.95	811.09	914.45	894.32	817.51	862.34
833.26	877.37	838.23	974.27	847.38	881.70	794.07	822.54	857.03	927.01
819.05	829.66	935.65	867.14	858.58	911.15	817.88	853.70	865.65	965.96
761.90	779.21	896.59	818.18	899.16	944.68	823.85	864.31	815.49	848.83
974.90	825.03	891.21	807.43	871.67	836.45	940.87	790.54	816.57	827.57
851.92	863.72	887.09	958.04	795.29	960.86	842.74	825.41	945.23	846.13
884.14	905.63	785.19	1015.05	791.30	925.19	803.97	931.45	823.61	843.53

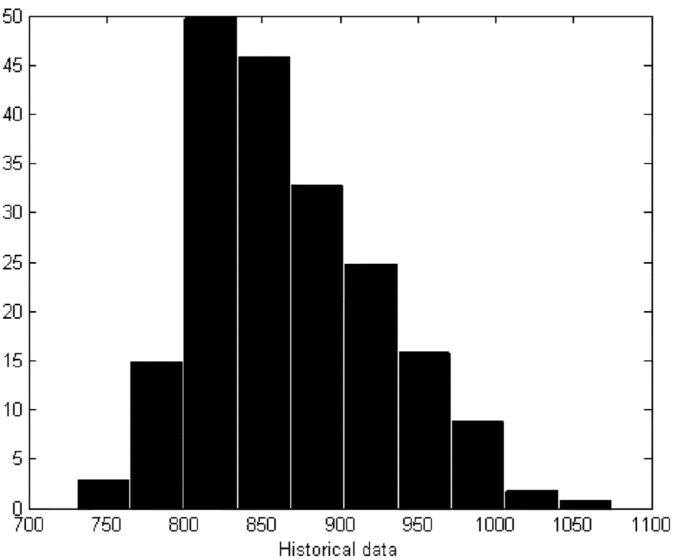

Fig. 6. Histogram of the 200 observations.

That is, we have an approximate $100(1-\alpha)\%$ upper confidence bound of CCT

$$CCT + z_{\alpha}\sqrt{\frac{S_{CWT}^2}{n}} \tag{14}$$

where z_α is the $100(1-\alpha)$ percentile of the standard normal $N(0,1)$ distribution, for which tables are widely available $[\Phi(z_\alpha) = \alpha]$, n is the sample size of waiting times, and $S_{CWT}^2 = \sum_{i=1}^{k} \hat{\eta}_i \hat{\beta}^2$ is the variance of the combined Gamma distribution of waiting time in the PBGA packaging process flow.

V. CYCLE TIME CALCULATION FOR PBGA PACKAGING PROCESS

In this section, we consider a real-world application taken from a PBGA packaging shop floor in a semiconductor packaging factory located in the Science-based Industrial Park in Hsinchu, Taiwan and investigate the applicability of the proposed model. For the example investigated, there are three product types of orders, namely, PBGA658, PBGA596, and PBGA292. An order involves five jobs which must be processed at all the ten operations, at where a set of identical machines are arranged in parallel at each operation in the shop floor. In the factory we investigated, a manufacturing execution system (MES) is applied to enhance the abilities of automation and data collections. To estimate the combined cycle time for the whole process flow, we collect the waiting times regarding the three product types in the shop floor from the MES. Table II displays the 200 observations of waiting times, collected from the historical data, at the wire bonding operation for PBGA596. The "minute" is used as the unit for process time and waiting time. Fig. 6 plots the histogram shown the collected data.

It is evident to conclude the data collected from the PBGA packaging factory is not normal distributed by observing the histogram in Fig. 6. The historical data indicates that the process is approximated by a Gamma distribution. The maximum-likelihood estimators (MLE) of η and β for the Gamma distribution are rather complicated and there is no explicit close form for the MLE of η. Therefore, we consider the method of moments. The parameters η and β of this Gamma process could be estimated from the historical data, giving $\hat{\eta} = 216.48$ and $\hat{\beta} = 4.5$.

To obtain the combined cycle time for the whole PBGA packaging process flow, we collected the historical data of waiting times for the three product types at the ten operations from the MES applied in the shop floor. Table III shows the order process time and Table IV presents the two essential statistical elements, average ($\overline{x}$) and variance (s^2) of the collected WT data at each operation in the whole PBGA packaging process flow.

Using the method of moment estimators, $\hat{\eta} = \overline{x}^2/s^2$ and $\hat{\beta} = s^2/\overline{x}$, we estimate the parameters for Gamma distributions fitted to WT of each product type in the PBGA packaging process flow. Table V displays the estimated shape parameters ($\hat{\eta}$) with fixing the scale parameter ($\hat{\beta}$) 5, 4.5, and 3 for product type PBGA658, PBGA596, and PBGA292, respectively.

Based on (10), we can obtain the value of the combined cycle time, 5447.45 min, for PBGA658 in the PBGA packaging

TABLE III
ORDER PROCESS TIMES FOR EACH PRODUCT TYPE AT EACH PBGA PACKAGING OPERATION

	Product type		
Operations	PBGA658	PBGA596	PBGA292
Wafer back grinding	9	10	8
Wafer mounting	12.5	8.5	11
Wafer sawing	17.5	19.5	15
Die bonding	43	36	39.5
Wire bonding	1137.5	990.5	496
Molding	77	74	78.5
Marking	31	28.5	22.5
Ball mounting	191	154.5	112.5
Singulation	54	51	49
Inspection	29.5	25.5	23

TABLE IV
THE AVERAGE ($\overline{x}$) AND VARIANCE (s^2) OF WT AT EACH PROCESS OPERATION

	PBGA658		PBGA596		PBGA292	
Operations	$\overline{x}$	s^2	$\overline{x}$	s^2	$\overline{x}$	s^2
Wafer back grinding	105.28	526.44	124.47	560.44	102.23	306.64
Wafer mounting	132.49	662.39	100.81	504.22	166.88	500.34
Wafer sawing	150.53	752.85	195.25	878.29	112.80	337.94
Die bonding	653.40	3263.99	624.63	2810.75	482.62	1449.09
Wire bonding	1171.58	5854.68	974.13	4383.56	830.91	2490.98
Molding	322.10	1611.81	381.60	1716.37	418.27	1255.63
Marking	219.34	1096.71	276.02	1242.41	371.68	1117.02
Ball mounting	516.94	2582.26	501.57	2257.04	421.34	1263.96
Singulation	308.88	1543.90	235.09	1057.56	218.36	654.83
Inspection	263.16	1314.83	186.84	841.47	147.42	441.54

TABLE V
ESTIMATED SHAPE PARAMETERS ($\hat{\eta}$) FOR FITTED GAMMA DISTRIBUTIONS OF WT

	Product type		
Operations	PBGA658	PBGA596	PBGA292
Wafer back grinding	21.05	27.64	34.08
Wafer mounting	26.50	20.15	55.66
Wafer sawing	30.10	43.41	37.65
Die bonding	130.80	138.81	160.74
Wire bonding	234.45	216.48	277.17
Molding	64.37	84.84	139.33
Marking	43.87	61.32	123.67
Ball mounting	103.49	111.46	140.45
Singulation	61.80	52.26	72.82
Inspection	52.67	41.49	49.22

factory. Similarly, the value of the combined cycle time for PBGA596 and PBGA292 can be obtained as 4988.37 and 4127.37 minutes, respectively.

Using the reproductive property of the Gamma distribution, the combined cycle time of PBGA658 has Gamma distribution and its corresponding parameters are Gamma (769.09, 5). Therefore, based on (14) for upper confidence bounds calculation, the 95% upper confidence bound of CCT for PBGA658 is 5463.58 min. That is, the combined cycle time for PBGA658 in the PBGA packaging process flow is not greater than 5463.58 min at 95% confidence. Similarly, 5003.16 and 4138.89 are the 95% upper confidence bounds of CCT for PBGA596 and PBGA292, respectively. We note that the upper confidence bounds can be used as a convenient reference point for assigning due dates and other planning bases in order to help the practitioners to provide an accuracy basis for due date assignment, production planning, and factory performance analysis.

VI. CONCLUSION

In this paper, we considered a statistical approach for cycle time estimation incorporating the upper confidence bounds in semiconductor PBGA packaging factories since the cycle time is an essential basis for production planning and due date assignment. We first provide a cycle time estimation model for single operation. Waiting times of each product type are modeled as Gamma distribution. We then present a combined cycle time estimation model which incorporates the reproductive property of Gamma distribution to estimate the whole factory cycle time for the multiple operations in the PBGA packaging shop floors. Moreover, upper confidence bounds at various confidence coefficients were also provided based on the investigated cycle time estimation model in order to quickly respond to the customer inquiries regarding due dates and shipping schedules. To demonstrate the applicability of the proposal estimation model, we considered a real-world example taken from a PBGA packaging shop floor in a semiconductor factory located in the Science-Based Industrial Park in Hsinchu, Taiwan. The computational results showed that the cycle time estimation model provided satisfactory values of cycle time. Therefore, we believe that the investigated cycle time estimation model incorporating upper confidence bounds may help industrial practitioners involved in PBGA packaging shop floor to estimate cycle time and to provide an accuracy basis for due date assignment, production planning, and factory performance analysis and to make judicious decisions.

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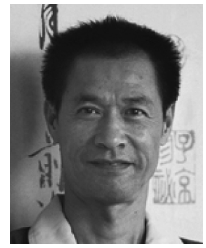

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