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Intelligent Production of Wire Bonds using Multi-Objective Optimization – Insights, Opportunities and Challenges

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Abstract

Ultrasonic wire bonding is an indispensable process in the industrial manufacturing of semiconductor devices. Copper wire is increasingly replacing the well-established aluminium wire because of its superior electrical, thermal and mechanical properties. Copper wire processes differ significantly from aluminium processes and are more sensitive to disturbances, which reduces the range of parameter values suitable for a stable process. Disturbances can be compensated by an adaption of process parameters, but finding suitable parameters manually is difficult and time-consuming. This paper presents a physical model of the ultrasonic wire bonding process including the friction contact between tool and wire. This model yields novel insights into the process. A prototype of a multi-objective optimizing bonding machine (MOBM) is presented. It uses multi-objective optimization, based on the complete process model, to automatically select the best operating point as a compromise of concurrent objectives.

Key words

wire bonding, multi-objective optimization, process model, copper wire, self-optimization

I. Introduction

Ultrasonic wire bonding is an indispensable process in the industrial manufacturing of semiconductor devices. It is used to electrically connect semiconductor chips to e.g. connectors or other chips in electronic modules. In high power applications, such as wind turbines, locomotives or electric vehicles, the wire bonds operate close to the thermal and mechanical limits of aluminium. Fig. 1 shows a wire bonding process on test substrate.

Copper wire is increasingly replacing the well-established aluminium wire because of its superior electrical, thermal and mechanical properties: Conductivity, melting point, and mechanical strength are higher, and the thermo-mechanical mismatch, i.e. the difference between coefficients of thermal expansion, is less pronounced in connection with silicon semiconductors (Si: 2.610^{6}/K), cf. table I. This results in higher ampacity, higher allowable operation temperature and longer lifetime. These benefits can only be brought to their full potential using improved chip-to-substrate joining technologies such as silver sintering [1, 2]. The continuous reduction of chip sizes (Fig. 2) also fuels the trend towards copper wire and for the fast-growing new generation of wide bandgap semiconductors based on Silicon Carbide (SiC) and Gallium Nitride (GaN), operating at junction temperatures of 175°C and beyond, copper wires as a top side connection are mandatory.

Table I: Material properties of aluminium and copper [3]

	Aluminium (Al)	Copper (Cu)
specific resistance	0,027 Ω mm^2 / m	0,017 Ω mm^2 / m
thermal conductivity	220 W / m K	400 W / m K
thermal expansion	23 10^{-6} / K	16,5 10^{-6} / K
yield strength	29 MPa	140 MPa
tensile strength	40 – 50 MPa	210 – 230 MPa
elastic modulus	70 GPa	110 – 140 GPa
melting point	600 °C	1083 °C

Due to the very different material properties, copper wire processes differ significantly from aluminium wire processes and are generally more challenging: Process forces and ultrasound power must be two to three times as high, which increases the risk of damaging the semiconductor or causing

delamination in lower layers. In combination with the hardness and abrasive characteristic of copper wire, increased force and vibration also significantly reduce the lifetime of standard consumables, so optimized consumables should be used [4]. Copper wire processes also are more sensitive to external disturbances, which reduces the range of parameter values suitable for a stable process, especially on the chip.

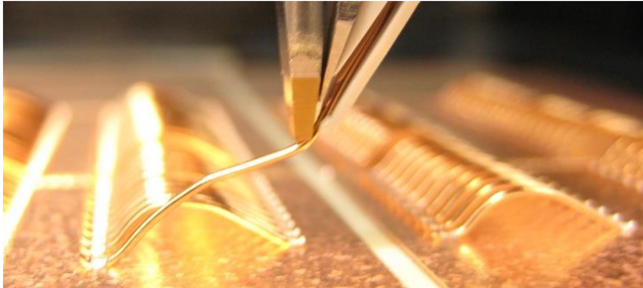

Fig. 1. Heavy copper wire bonding on test substrate

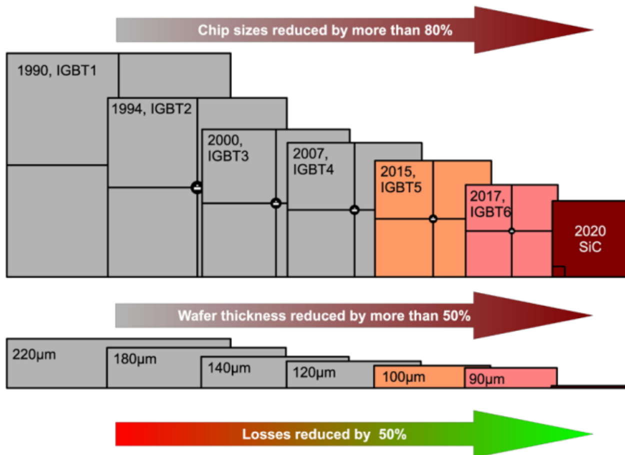

Fig. 2. Development of chip size and thickness [5]

Additionally, copper wire bond reliability is limited by the sensitivity of the manufacturing process to external disturbances. In order to increase reliability, these influences can be compensated by an online-adaption of process parameters. But finding suitable parameters manually is difficult and time-consuming because of the high number of possible parameter combinations and the complex interaction between the individual parameters. This is the motivation to develop a multi-objective optimizing bonding machine (MOBM), which determines Pareto-optimal operating points and the associated process parameters and implements these parameters online [6].

II. Modelling of the Ultrasonic Wire Bonding Process

The basic prerequisite for model-based optimization is a complete behaviour model, which can be seen schematically in Fig. 3. The general outline of the model was introduced before in [7]. It models the effects of actual process parameters, such as normal force, ultrasonic voltage amplitude and process duration, on characteristic properties of the bond, like friction forces and local adhesion in the bond interface. It is important to note that process parameters of the model correspond to actual bonding machine process parameters. As objectives, *duration of the process*, *wear of the tool*, *severity of tool-substrate contacts* and *bond strength* were determined. After each process model simulation, objective function values are computed.

A. Determination of contact area

The objective *bond strength* is strongly determined by the effective contact area. The contact area is mainly influenced by wire deformation: As the wire flattens, the contact area increases. Wire deformation is measured in the bonding machine as the vertical displacement of the bonding tool after the vertical force in the substrate-wire-tool contact exceeds a defined initial force ("touchdown"). This has been modelled using finite element method (FEM), which results in the contact area as a function of wire height. During FE-simulation of the bonding process, wire height is an input parameter of the model which returns pressure distribution in a discretized contact area.

The wire height is computed by a machine learned model for the ultrasonic softening effect which has also been introduced before [8]. It takes the process parameters as inputs and models the transient wire softening during application of ultrasonic vibration. If the deformation of the wire has reached a critical value, the tool tip touches the substrate during bonding (objective *tool-substrate contacts*).

B. Process dynamics

With a known pressure distribution determined using FEM, the bond formation process in substrate and wire can be modelled. The most important driver of bond formation is mechanical friction energy dissipated in the contact area, other minor drivers are thermomechanical forces and inner friction [9]. To calculate this process, the mechanical vibrations need to be simulated using a combination of transducer, substrate and friction contact models.

The transducer is excited by an ultrasonic voltage, which oscillates with the systems eigenfrequency and thus keeps the whole process in resonance in order to achieve high electromechanical energy conversion efficiency. This is achieved by a phase locked loop controller (PLL) in both the actual bonding machine and in the process model. It measures the phase shift between electric voltage and current and adapts the frequency after each simulated cycle such that the phase shift always tends to zero. The actual bond formation is modelled with a friction model, dividing the contact area into individual elements and allows highly detailed insights into the process. This model is very complex and simulating full time would be very time consuming [9]. Instead, a reduced model is used, which is parameterized by on demand evaluation of

the full model. By this it the simulation time could be reduced by more than a decade without losing significant accuracy. The ultrasonic transducer is modelled as a linear system as introduced in [10].

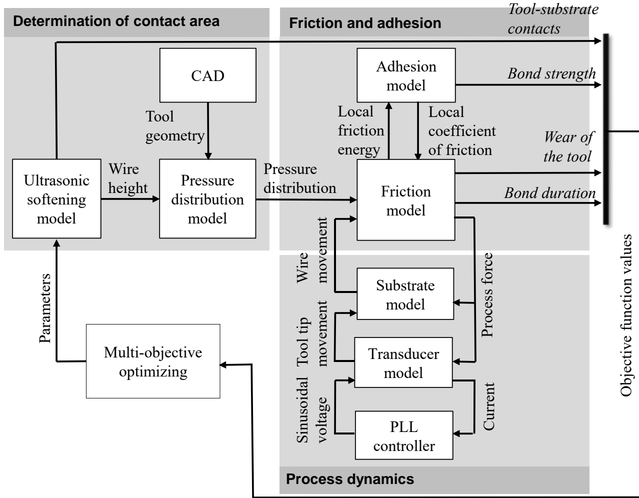

Fig. 3. Flowchart of the ultrasonic wire bonding process model [11]

C. Friction and adhesion

The ultrasonic wire bonding process is a cold friction welding process. The joining partners are pressed together while the ultrasonic vibration of the transducer creates a relative movement in the interface of the contact. The resulting friction energy drives the joint formation between both partners. This is modelled by increasing the friction coefficient as a function of the calculated friction energy. The bonding of the metallic material happens at the atomic level. Adhesion patterns depicted in Fig. 4(a-f), which were introduced in [12], were obtained by applying a suitable image processing to microscope images of bond interfaces after pull test. They show the probability of friction welded partial areas (0 to 100 % bonded) at different points in time during bonding. At the beginning of the process, the wire comes into contact with the substrate due to the normal force and a small elliptical contact is created. First micro welds (100% bonded) can be observed in Fig. 4(c) after 45 ms of bonding, close to the upper and lower boundary of the contact area. It is apparent that local frictional power is highest at the periphery of the contact area. With increasing duration, an elliptical "bonded" area of high weld probability is formed (see at time 210 ms). The rate of bonded area growth correlates strongly with the growth of shear strength [12].

Althoff et al. [9] have described this bond formation using a model which divides the contact area into multiple partial areas. Each partial area is modelled as a point contact element and has a corresponding normal force, friction coefficient and degree of freedom. The model calculates the cleaning and adhesion state from the applied frictional energy. The sum of all friction elements represents the behaviour of the entire contact. This model describes the bonding behaviour in detail for the contact between wire and substrate.

Fig. 5, also introduced in [12], shows simulation results corresponding to the experimental results in Fig. 4. The growth of micro welds starts at the outer rim of the initial contact area and progresses mainly towards the centre. Using the material shear strength of copper and the determined friction welded areas of the model, the maximum bond strength of the contact can be calculated. Agreement between experimental and simulation results is satisfactory.

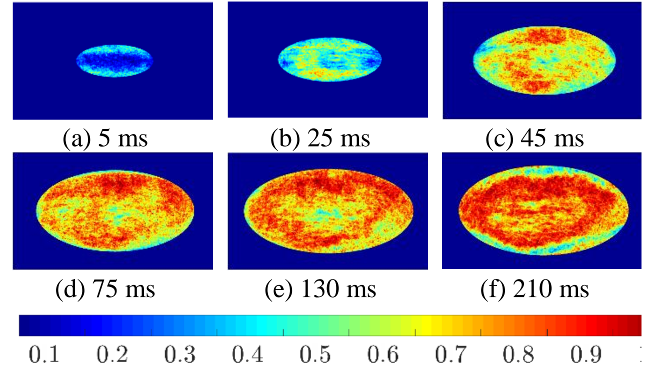

Fig. 4. Comparison of the probability of friction welded partial areas at different time steps (experiment) [12]

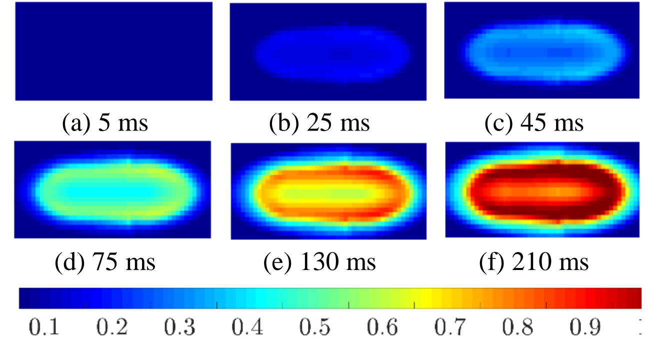

Fig. 5. Comparison of the probability of friction welded partial areas at different time steps (simulation) [12]

III. Multi-objective Optimization for the Wire Bonding Process

The copper wire bonding process requires carefully tuned parameters for proper functioning and high yield. The current state of the art is to use DOE (design of experiments) investigations, which are essentially structured trial-and-error using actual experiments and result evaluations. This is time consuming, because experiment supervisory personnel need to produce a large number of bond connections and do destructive testing on a statistically significant amount of these. This manual work takes weeks to find good parameters, which are then only valid for machines of the same type, wire-substrate-combination and clamping aperture.

Model-based multi-objective optimization techniques, on the other hand, allow completely automated virtual tests with the

process model. They aim to find minima of objective functions by adapting parameters of the process model. For conflicting objectives, a common minimum does not exist; instead, they find several possible trade-offs, called Pareto-optimal points or the Pareto front. For each of these trade-offs, the corresponding parameters are included in the Pareto set. Fig. 6 shows the dependence of selected, clearly conflicting objectives. It is well recognizable that Pareto-optimal points (highlighted in red) lie in the range of all possible compromises. Increasing of the bond duration or the ultrasonic voltage improves the strength (the numerical value is negative and decrease in order to comply with the convention that optimization problems are always minimization problems) while the wear gets worse (negative lifetime of the tool increases). In both cases, the frictional power increases with the increase of the respective parameter. Consequently, the surface elements bond faster. A trend can also be recognized for the probability of tool-substrate contacts. An increased severity of tool-substrate contacts (0 %: no tool-substrate contact, 100 %: tool-substrate contact with every bond, >100 %: more severe tool-substrate contact with every bond) occurs with increasing ultrasonic voltage in the bonding process. Classical design of experiments and manual evaluation of bond results would have been an immense effort for such a larger number of parameter combinations.

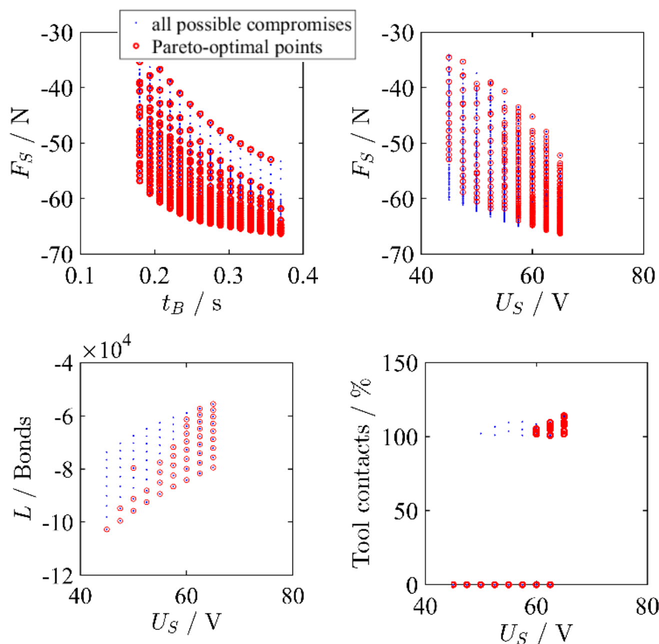

Fig. 6. Interactions of the objectives bond strength F_S, bond duration t_B, tool lifetime L and severity of tool-substrate contacts [11]

IV. Process Observer

As a precondition for a closed-loop multi-objective optimizing system behaviour of the whole bonding machine, the current state of the production process needs to be determined. This needs to correspond to the model-based description of the interdependencies between optimization objectives, and has to yield information about the actual *process duration*, *tool wear*, *probability of tool-substrate contacts* and *bond strength*.

1) Duration of the process: Information about the duration of the process is directly included in process parameters, mainly in the duration of voltage and force trajectories.

2) Wear of the tool: Wear of the tool is a significant cost driver for copper wire bonding. Sliding of the tool on the hard wire results in a distinctive wear of the groove geometry.

Estimation of the wear rate of the tool is challenging. In the scope of this work, we used the concept of so-called Health Indices *HI*. A Health Index is a quantitative measurement of the deviation of some sensor data acquired during bonding from previously learned reference data [13]. In this case, the sensor signal of the vertical movement of the tool is sufficiently sensitive to tool wear to assess the state of wear [4]. Fig. 7 shows the Health Index for a standard copper wire bond tool made of cermet over the production of 85.000 single bonds. A Kalman filter compensates for stochastic variation of the signal. Despite the variation, a reduction in signal value can be observed. To use this method for tool life prediction, the process parameters need to be constant, whereas the basic concept of a self-optimizing bonding machine includes autonomous parameter adaptation and is thus contradictory. To overcome this discrepancy, dedicated reference bonds with static parameters are used for estimation of the tool life. In addition, the frequency of tool-substrate contacts is a good indicator of the tool lifetime, especially at a late stage of life.

3) Tool-substrate contacts: A method for determining the probability of tool-substrate contacts was developed and validated. It is based on finding specific features in the signals provided by the machine-integrated quality control system ("PiQC"). This permits the detection of tool-substrate contacts for each bond and the time at which they occurred during the process. The occurrence increases with tool age mainly due to abrasion of tool material – the groove gets deeper, more volume of the wire flows into the opening, and the tool position is lower.

4) Bond strength: A current value of bond strength or the corresponding actual bonded area for each bond is also required for behaviour adaptation. At this time, an automatic measurement of the bond strength or bonded area is not possible because of the high complexity of the process itself. While the machine-integrated quality control system ("PiQC") is successfully used to determine the quality of each bond made and is nondestructive [13], its algorithms are based on finding the similarity between the current bond and given teach bonds. With this approach, it is limited to detecting deviations from the teach bonds and is thus not suitable for online parameter adaptation, where teach bonds would

have to be made for arbitrary process parameters. Instead, bond strength as the actual objective is measured directly in larger intervals. This can be done either using shear tests or pull tests. Both values depend on the size of the bonded area and on local bond strength. During experimental validation of the multi-objective optimizing bonding machine, we selected to use shear tests for their good repeatability and fast execution. The shear strengths of a set of sample bonds are captured in regular intervals. This way, a multi-objective optimizing bonding machine receives up-to-date information about bonds created with arbitrary adapted parameters.

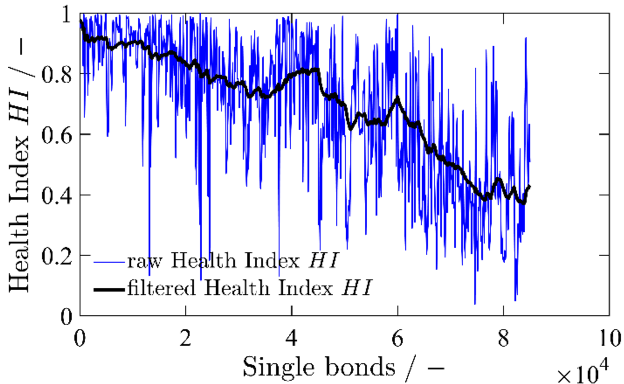

Fig. 7. Course of raw Health Index HI and derived tool wear monitor signal (filtered HI) [11]

V. Closed-loop Control

To achieve the proposed increase in bond reliability, online-parameter adaptation is used. The implemented multi-objective optimization process is made up of three separate steps. At first, the process observer described in Section IV evaluates measurement values and returns information about the current process state and the degree of fulfilment of the desired objectives. In the next step, it is compared to the desired objective values. A new working point is then selected from the results of the multi-objective optimization, see Section III. The parameters in the process control are adapted accordingly. After a set time interval, the adaptation cycle starts again.

These three steps are implemented on different computer systems. Measurement data is acquired by the machine automatically as part of its PiQC system and is transmitted to an external process and production data acquisition system ("PBS"). Both components are standard equipment on Hesse Mechatronics bonding machines, and extraction of raw measurement data for external evaluation is used. The second step is implemented on an external computer system. It forms the core of the optimization setup. Due to its prototypical character, Matlab to join all new major components, i.e. model-based multi-objective optimization, process observer, comparison of objectives and parameter selection, in one environment. The third step required an adapted bonder firmware. New parameters are requested from the PBS in regular intervals and these parameters are set for subsequent bonds.

VI. Conclusion and Outlook

The use of copper in heavy wire bonding has big advantages like high electrical and thermal conductivity and mechanical stability. But these advantages come at the cost of a production process that is more sensitive to parameter changes and variations in the environment. It was therefore desired to introduce a multi-objective optimizing bonding machine (MOBM) which could compensate such influences. This was achieved by first setting up a detailed model of the bonding process, which can be used to calculate the relevant objectives *bond strength*, *tool wear*, *tool-substrate contacts* and *bonding duration*. The presented model is used to compute trade-offs between these conflicting objectives. During operation, the currently best-suited operating point of the bonding machine can be selected, which in turn determines the process parameters. The four objectives can be prioritized online by the user. The system behaviour can be observed in graphs and histograms of the objective functions and in basic process signals.

One major goal of developing a MOBM was a compensation of perturbations without expensive testing and experience. This way, the complexity of machine operation is reduced. Evaluation of the finished prototype shows that this goal was reached. More investigations using this successful prototype implementation are planned to show its potential as a future new standard in production.

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