# Learning for motion control in bonding machines: Bridging data-driven learning and physical modelling

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# Learning for motion control in bonding machines: Bridging data-driven learning and physical modelling*

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Semiconductor back-end machines require high position accuracy, throughput, and reliability in a variety of industrial environments. Motion control is essential to meet future challenges. Systems have to perform varying motion tasks with (sub-)micrometer precision. The high demands on throughput require movements with high velocity and accelerations. Robustness and reliability for changing industrial environments is needed to minimize machine-to-machine differences and obtain uniform system performance. The use of data-driven learning in conjunction with model-based control approaches is envisaged to overcome these challenges.

Regarding the first challenge, fast and safe learning is required while maintaining flexibility under varying motion tasks. Traditional ILC enables high performance with fast and safe learning for repeating motion [1]. Advanced ILC algorithms are required for operation for varying motion tasks. Herein, the feedforward signal is parameterized by basis functions that incorporate model knowledge [2]. Traditionally, the basis functions are chosen using typical motion profiles, i.e., velocity, acceleration, and snap. For semiconductor back-end machines, substantial non-linear dynamics are present. Therefore, non-linear terms are included in the basis functions, which are derived from first principle modelling of the system. Experimental tests on a XYZ-motion stage of a commercial wirebonder shows significant performance improvement despite varying motion tasks.

Ongoing research to futher improve the performance focusses on multipe aspacts. First, the basis functions are extended to further reduce the error up to the reproducible part using a data-driven approach. Special attention is given to interaction between axis and position- and time-dependent system dynamics [3]. Secondly, unmeasured performance evaluation at the bonding location is investigated. Thirdly, the necessity of a model for fast and safe learning is revisited by applying model-free learning using reinforcement learning techniques to enhance performance under changing environments. To conclude, these techniques combined bridge data-driven learning with physical modelling.

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