

Multibody System Dynamics Throughout the Product Lifetime

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ABSTRACT

Traditionally, multibody system dynamics has been used as a tool to expedite product development processes and to enhance product quality. In this study, its use is extended beyond the product development phase to cover the entire product lifetime. It highlights how multibody system dynamics improves the understanding of product usage, customers and production, and boosts service-based businesses.

This extension is significant because traditional material-based business processes, i.e. product manufacturing, are being supplemented by models based on data and knowledge processing. These new business models seem to complement traditional economic theories such as the concept of diminishing returns [1], and reviews of digital servitization report a rapid growth of data-driven solutions in manufacturing together with a positive influence on firm performance and profitability. Multibody system dynamics therefore plays a critical role in building businesses related to data and knowledge processing.

Several examples are provided. Multibody system dynamics is used in gamification as part of product development [2]. Extending simulation to the operational phase requires computational performance: recent formulations, such as the Lie-theoretic double-step semi-recursive method, improve efficiency and precision in systems with many bodies and closed loops, making real-time capable models attainable [3]. Such models can be integrated with real machines using a concept called reality-driven simulation, in which the multibody system model is actuated via sensor signals coming from the operating machine [4].

The study also covers how artificial intelligence can control multibody system models and how the data required for training the artificial intelligence can be generated by the models themselves [5]. This is particularly relevant for maintenance: measured failure data are scarce and costly, whereas physics-based and hybrid synthetic data support condition monitoring, anomaly detection and remaining-useful-life prediction, and thus service models such as maintenance-as-a-service [6]. Individual model components can also be data-driven; neural-network surrogates can replace analytical friction models when their input-output design is physically informed [7].

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