Remaining useful life (RUL) prediction plays a crucial role in maintaining the operational efficiency, reliability, and performance of complex engineering systems. Recent efforts have primarily focused on individual components or subsystems, neglecting the intricate relationships between components and their impact on system-level RUL (SRUL). The existing gap in predictive methodologies has prompted the need for an integrated approach to address the complex nature of these systems, while optimizing the performance with respect to these predictive indicators.

This thesis introduces a novel methodology for predicting and optimizing SRUL, and demonstrates how the predicted SRUL can be used to optimize system operation. The approach incorporates various types of data, including condition monitoring sensor data and component reliability data. The methodology leverages probabilistic deep learning (PDL) techniques to predict component RUL distributions based on sensor data and component reliability data when sensor data is not available. Furthermore, an equation node-based Bayesian network (BN) is employed to capture the complex causal relationships between components and predict the SRUL. Finally, the system operation is optimized using a multi-objective genetic algorithm (MOGA), where SRUL is treated as a constraint and also as an objective function, and the other objective relates to mission completion time. The validation process includes a thorough examination of the component-level methodology using the C-MAPSS data set. The practical application of the proposed methodology in this thesis is through a case study involving an unmanned surface vessel (USV), which incorporates all aspects of the methodology, including system-level validation through qualitative metrics. Evaluation metrics are employed to quantify and qualify both component and system-level results, as well as the results from the optimizer, providing a comprehensive understanding of the proposed approach's performance.

There are several main contributions of this thesis. These include a new deep learning structure for component-level PHM, one that utilizes a hybrid-loss function for a multi-layer long short-term memory (LSTM) regression model to predict RUL with a given confidence interval while also considering the complex interactions among components. Another contribution is the development of a new framework for computing SRUL from these predicted component RULs, in which a Bayesian network is used to perform logic operations and determine the SRUL. These contributions advance the field of PHM, but also provide a practical application in engineering. The ability to accurately predict and manage the RUL of components within a system has profound implications for maintenance scheduling, cost reduction, and overall system reliability. The integration of the proposed method with an optimization algorithm closes the loop, offering a comprehensive solution for offline planning and SRUL prediction and optimization. The results of this research can be used to enhance the efficiency and reliability of engineering systems, leading to more informed decision making.