Health monitoring and prognostics are key process for condition-based maintenance (CBM) in many application domains where safety and reliability of systems are considered essential requirements. CBM programs greatly reduce costs by helping to avoid catastrophic failures and by scheduling the appropriate maintenance actions in an efficient way. Mechanical systems often operate under varying operational and environmental conditions, and their failure mechanisms usually involve several degraded health-states. The estimation and monitoring of those health-states and incipient fault evolution, together with the assessment of remaining useful life (RUL) of the system is a critical challenge of CBM. In addition, the machine components’ behavior is subject to high uncertainty and unpredictability so that effective methods for its online health prognosis are still under development. As a result different approaches and techniques have been developed in the last decade for RUL estimation; one of them is based on hidden Markov models (HMMs); this methodology has demonstrated to be a well-suited procedure to estimate unobservable states using observable sensor signals, and thus have been used to perform detection and estimation in machine prognostics. However, it has several disadvantages: a) it has limited power when modeling temporal structures due to the independence on the past history caused by Markov property; b) it is difficult to obtain an explicit distribution of the RUL in a closed form; c) there exists a lack of relations of the defined health-state change point to the actual defect progression, among others. To address some of these shortcomings, this paper presents a fuzzy hidden Markov model (FHMMs) prognostics method for machine health forecasting, which has been effectively used in the past for handwriting, speech and human motion recognition problems. Unlike previous HMMs, the main characteristic of the proposed method is the relaxation of the usual additive constraint of probability measures required for classical HMMs, by incorporating fuzzy integrals and fuzzy measures, as a result the statistical independence assumption of the traditional HMMs is relaxed. Another interesting advantage is that the nonstationary behavior is achieved naturally, important characteristic since the transition probabilities vary with time. Moreover, it does not require fixing the lengths of the observation sequences and the availability of more training data in order to learn a large number of transition parameters. The proposed method is tested using an experimental vibration data-set in order to demonstrate its performance.