Kernel partial least squares (KPLS) models are widely used as nonlinear data-driven methods for faults detection (FD) in industrial processes. However, KPLS models lead to irrelevant performance over long operation periods due to process parameters changes, errors and uncertainties associated with measurements. Therefore, in this paper, two different interval reduced KPLS (IRKPLS) models are developed for monitoring large scale nonlinear uncertain systems. The proposed IRKPLS models present an interval versions of the classical KPLS model. The two proposed IRKPLS models are based on the Euclidean distance between interval-valued observations as a dissimilarity metric to keep only the more relevant and informative samples. The first proposed IRKPLS technique uses the centers and ranges of intervals to estimate the interval model, while the second one is based on the upper and lower bounds of intervals for model identification. These obtained models are used to evaluate the monitored interval residuals. The aforementioned interval residuals are fed to the generalized likelihood ratio test (GLRT) chart to detect the faults. In addition to considering the uncertainties in the input-output systems, the new IRKPLS-based GLRT techniques aim to decrease the execution time when ensuring the fault detection performance. The developed IRKPLS-based GLRT approaches are evaluated across various faults of the well-known Tennessee Eastman (TE) process. The performance of the proposed IRKPLS-based GLRT methods is evaluated in terms of missed detection rate, false alarms rate, and execution time. The obtained results demonstrate the efficiency of the proposed approaches, compared with the classical interval KPLS