We study anomaly detection for fast streaming temporal data with real time Type-I error, i.e., false alarm rate, controllability; and propose a computationally highly efficient online algorithm, which closely achieves a specified false alarm rate while maximizing the detection power. Regardless of whether the source is stationary or nonstationary, the proposed algorithm sequentially receives a time series and learns the nominal attributes-in the online setting-under possibly varying Markov statistics. Then, an anomaly is declared at a time instance, if the observations are statistically sufficiently deviant. Moreover, the proposed algorithm is remarkably versatile since it does not require parameter tuning to match the desired rates even in the case of strong nonstationarity. The presented study is the first to provide the online implementation of Neyman-Pearson (NP) characterization for the problem such that the NP optimality, i.e., maximum detection power at a specified false alarm rate, is nearly achieved in a truly online manner. In this regard, the proposed algorithm is highly novel and appropriate especially for the applications requiring sequential data processing at large scales/high rates due to its parameter-tuning free computational efficient design with the practical NP constraints under stationary or non-stationary source statistics.