Deep Learning Based Nonlinear Principal Component Analysis for Industrial Process Fault Detection

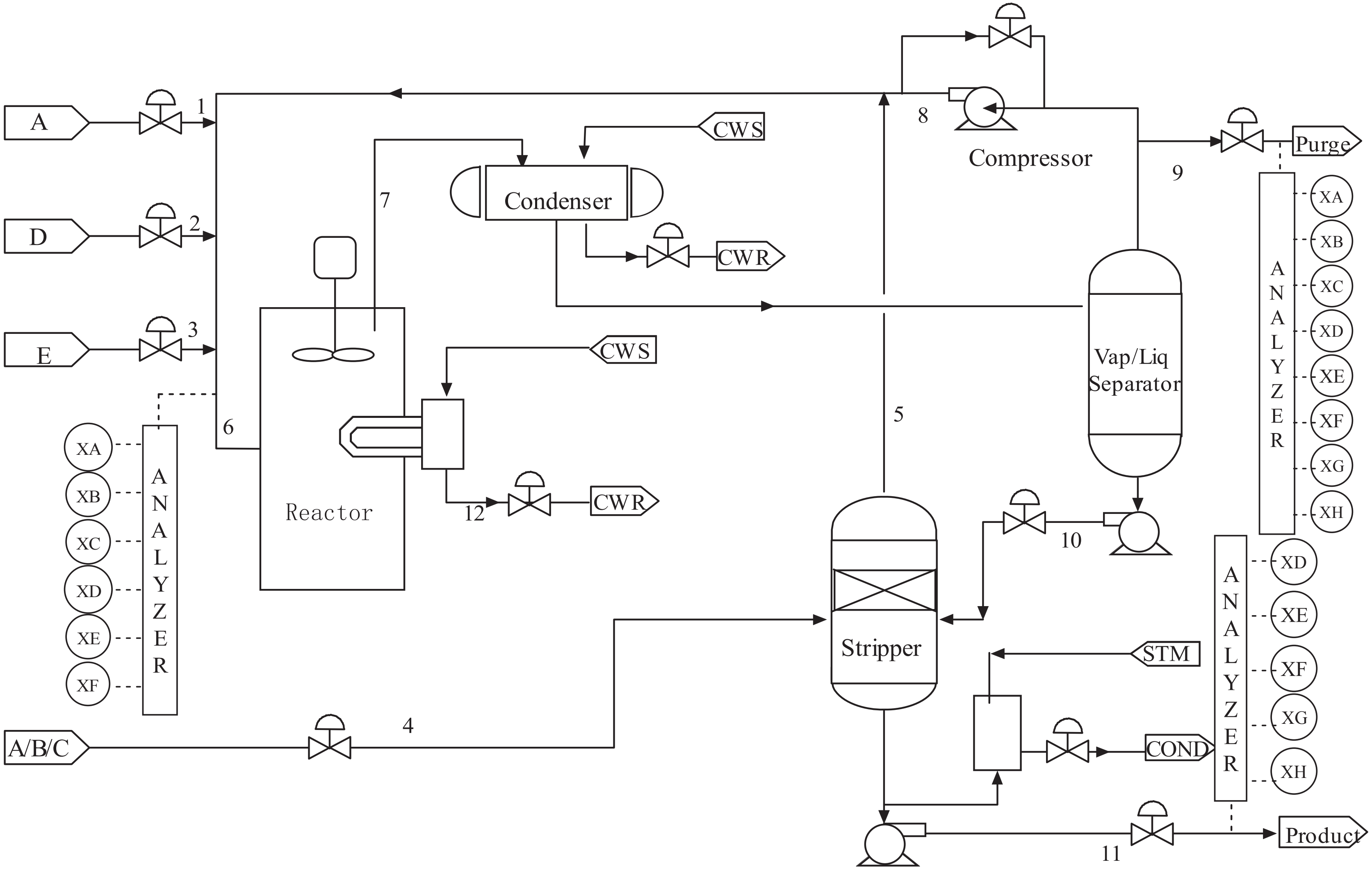
Xiaogang Deng[1], Xuemin Tian[1], Sheng Chen[2], Chris J. Harris[2]

[1]College of Information and Control Engineering, China University of Petroleum, Qingdao 266580, China

[2]School of Electronics and Computer Science, University of Southampton, Southampton SO17 1BJ, UK

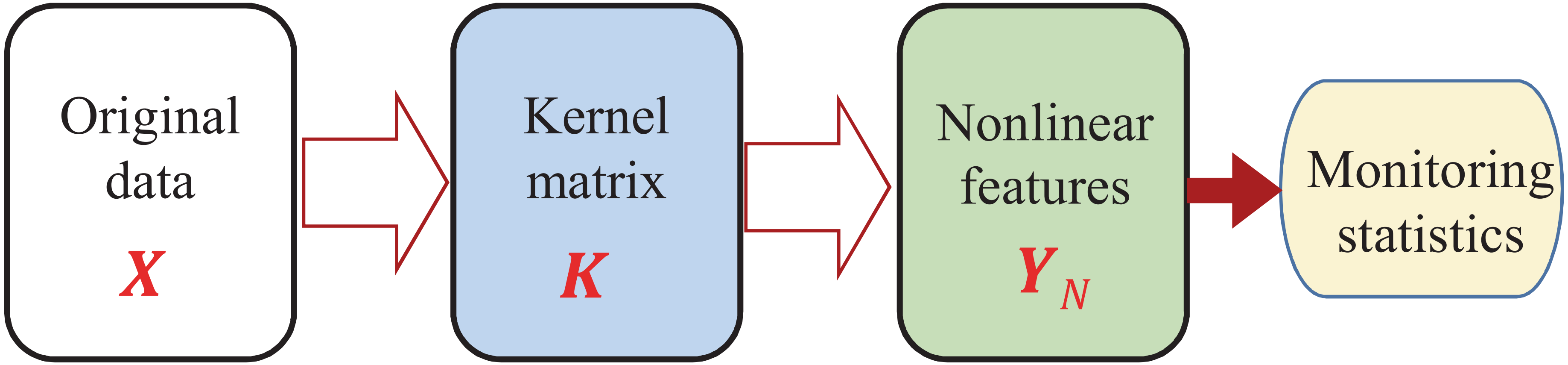
Fault Detection

- **Process monitoring** plays a key role in enhancing industrial plant **safety**, reducing production **cost**, and improving product **quality**



KPCA

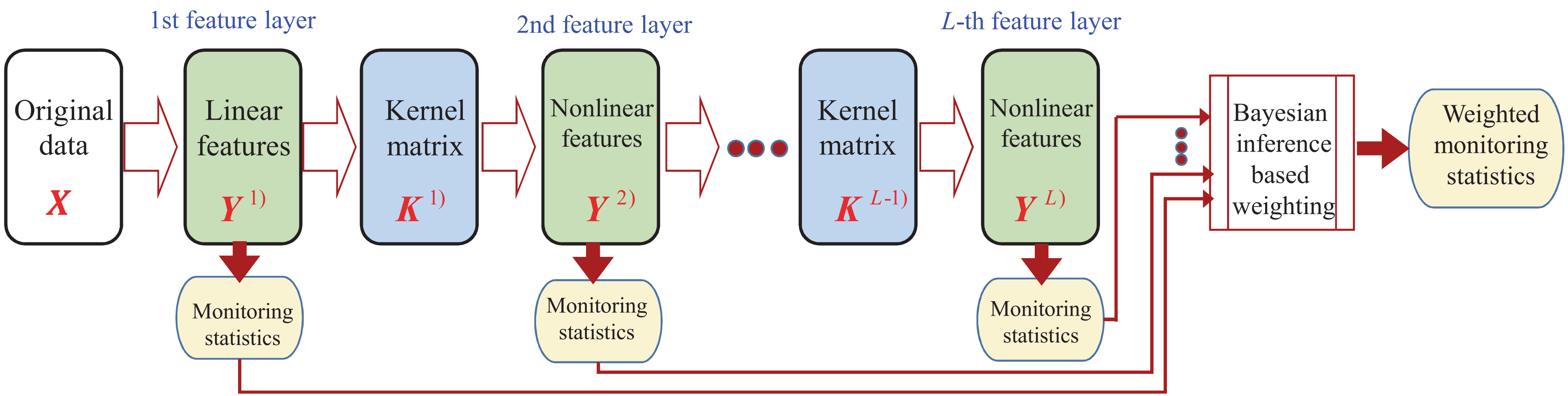
- Existing state-of-the-art is based on **kernel principal component analysis**
  - Widely applied to **nonlinear** and **non-Gaussian** industrial process monitoring



- KPCA statistical modeling extracts **single** layer of nonlinear features
  - A '**shallow**' learning
  - May be insufficient to mine **intrinsic** hidden data features

DePCA

- Inspired by **deep learning** strategy, we propose a deep learning inspired nonlinear PCA method, referred to as DePCA



- **DePCA** statistical modeling consists of $L \geq 2$ **layers** of feature extraction
  - 1st PCA layer extracts **linear features**
  - the following $(L-1)$ KPCA layers extracts **nonlinear features**
  - Bayesian inference weights monitoring statistics constructed from different layers to yield overall **weighted monitoring statistics**

Issues Related to DePCA

- **How deep** should DePCA be: problem dependent
  - **Simplest** DePCA: $L = 2$, a PCA linear layer followed by a KPCA nonlinear layer
- **What kernels** to use at different KPCA layers: e.g., Gaussian, polynomial
  - For '**diversity**', different KPCA layers can adopt different kernels
- Like KPCA based method, implementation of DePCA involves
  - **Offline training** stage: normal operation data divided into training set, for statistical modeling, and validation set, for computing 95% confidence limits
  - **Online monitoring** stage: monitoring statistics are constructed from features extracted from real-time sample for fault detection
- **Online complexity**: DePCA with $L = 2$ similar to KPCA, as complexity of linear PCA is negligible, while DePCA with $L = 3$ is approximately twice of KPCA

Benchmark Process

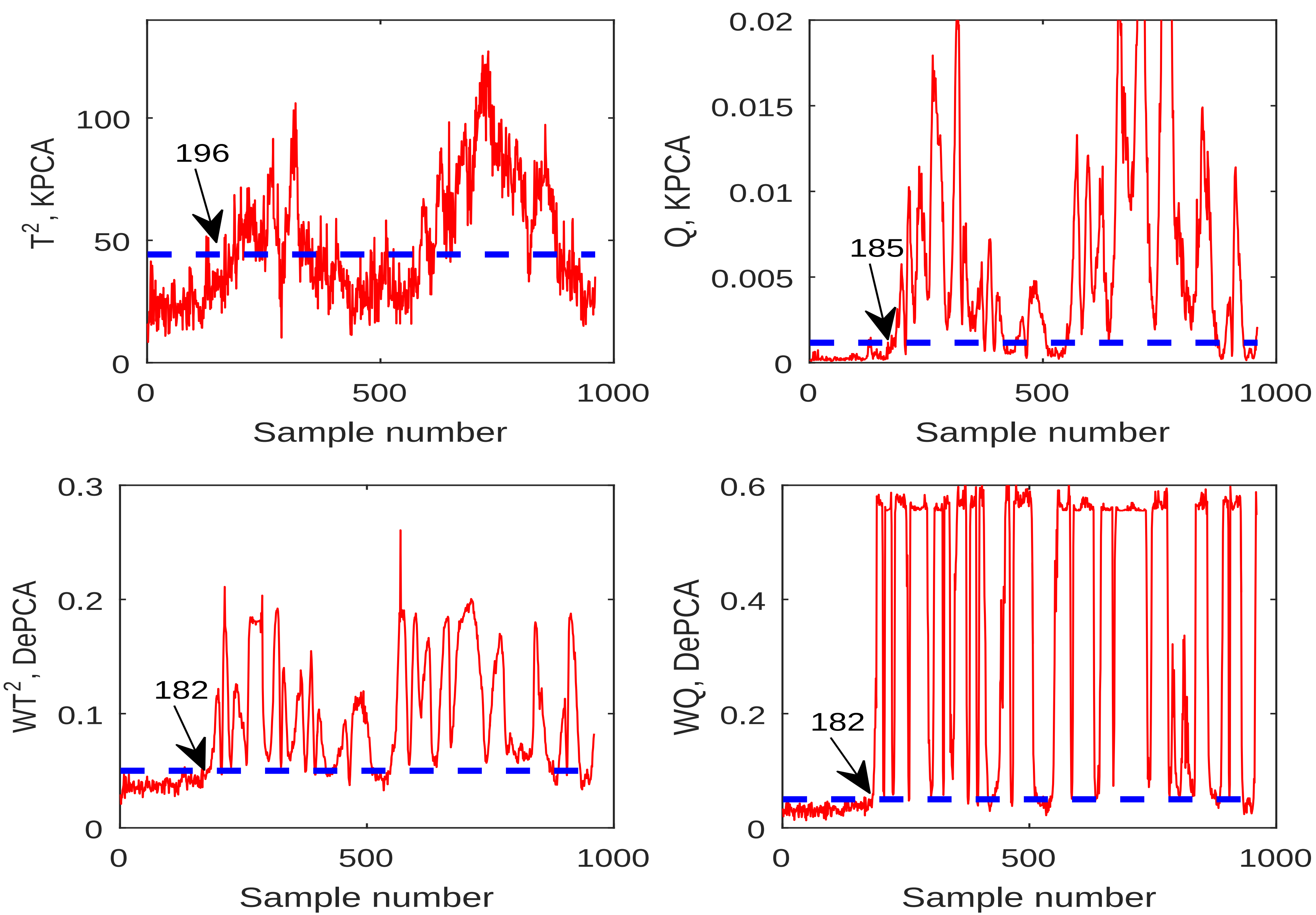
- Tennessee Eastman process (page 2) simulates **a real chemical process** which involves five major units: reactor, condenser, compressor, stripper and separator
- Monitored 33 variables consist of 22 process measurement variables and 11 manipulated variables
- 1460 normal operation samples are divided into **training set** of 500 samples and **validation** set of 960 samples
- **Ten faults** as listed in next page are tested, and each fault dataset contains 960 samples with fault introduced at 160th sample
- KPCA with Gaussian kernel and DePCA of $L = 2$ also with Gaussian kernel are compared
- Standard **T^2 and Q monitoring statistics** are used by KPCA, while DePCA adopts **weighted T^2 and Q monitoring statistics**

Fault label	Description	Fault code	Type
F1	A/C feed ratio(stream 4)	IDV1	**Step**
F2	Reactor cooling water inlet temperature	IDV4	**Step**
F3	Condenser cooling water inlet temperature	IDV5	**Step**
F4	C feed temperature (stream 4)	IDV10	**Random**
F5	Reactor cooling water inlet temperature	IDV11	**Random**
F6	Unknown fault	IDV16	**Unknown**
F7	Unknown fault	IDV17	**Unknown**
F8	Unknown fault	IDV19	**Unknown**
F9	Unknown fault	IDV20	**Unknown**
F10	Stream 4 valve	IDV21	**Sticking**

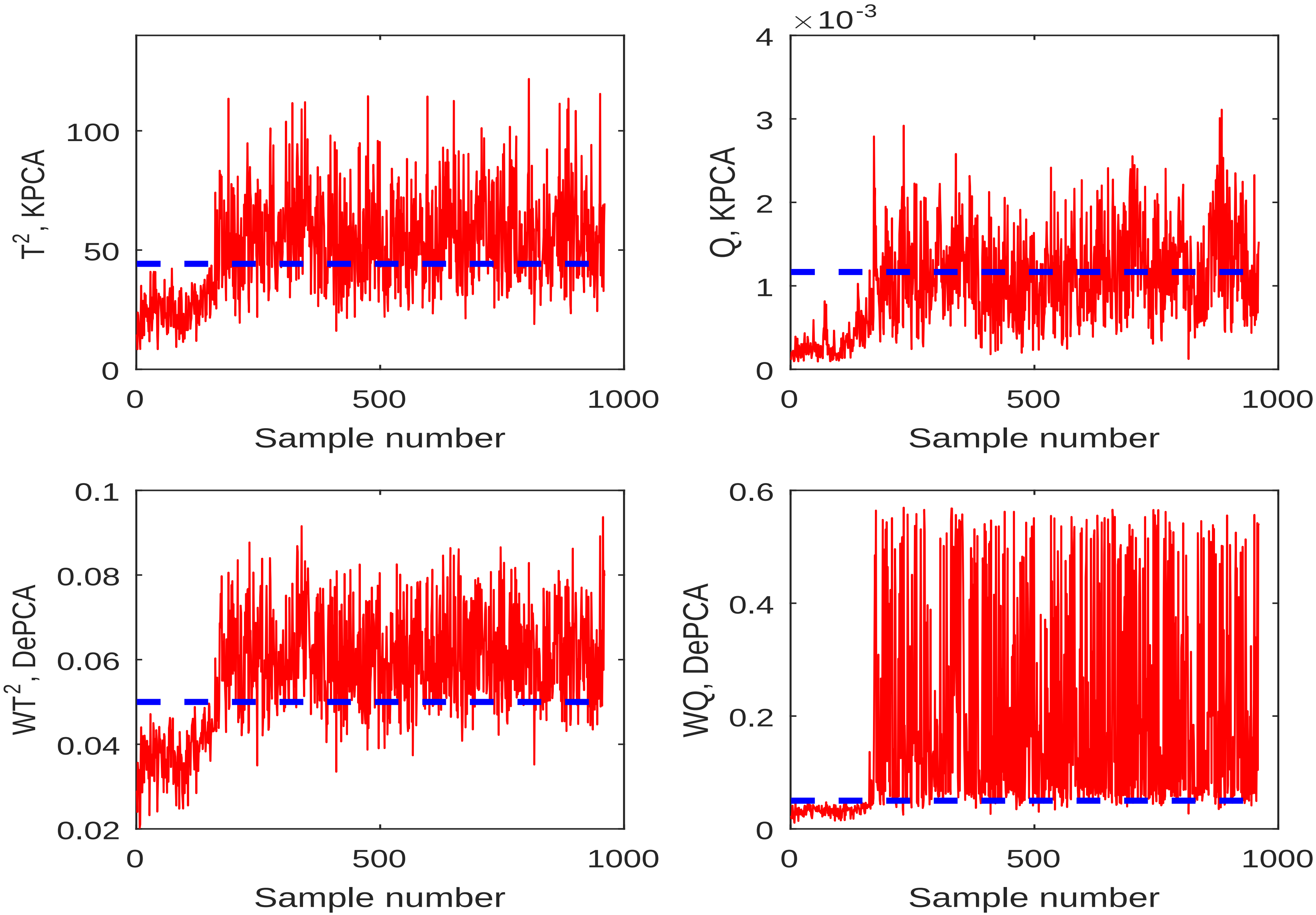
- Average **false alarming rates** (%) of the normal operation parts of tested datasets obtained by KPCA and DePCA, all below 5%, consistent with 95% confidence

Method	**KPCA**		**DePCA**	
Monitoring statistics	T^2	Q	WT^2	WQ
FAR	3.9	3.1	2.1	2.2

Fault F4 Detection Results



Fault F8 Detection Results



Fault Detection Rates (%)

Fault Label	KPCA		DePCA	
	T^2	Q	WT^2	WQ
F1	100	99.6	99.9	100
F2	100	83.5	98.6	100
F3	29.1	81.0	29.6	100
F4	56.1	81.0	86.5	88.8
F5	84.1	66.6	71.6	81.8
F6	38.5	85.5	89.3	91.6
F7	90.6	90.3	94.9	96.6
F8	68.5	48.5	83.8	90.3
F9	73.4	65.4	88.4	90.8
F10	59.5	42.8	51.4	61.3
Average	**70.0**	**74.4**	**79.4**	**90.1**

Fault Detection Times (sample number)

Fault Label	KPCA		DePCA	
	T^2	Q	WT^2	WQ
F1	161	164	162	161
F2	161	163	163	161
F3	161	161	161	161
F4	196	185	182	182
F5	166	171	166	166
F6	350	171	170	167
F7	182	184	182	182
F8	223	300	171	170
F9	239	238	230	230
F10	416	637	571	416

All fault occur at 160th sample

Summary

- We have proposed a **deep learning** inspired nonlinear PCA method called **DePCA** for industrial process **monitoring**
  - Our initial investigation demonstrates that **DePCA** **outperforms** the existing state-of-the-art **KPCA** method
- This opens a **new research** direction for applying deep learning strategy to monitor nonlinear and non-Gaussian **industrial processes**
  - Further researches are warranted to develop DePCA, including how '**deep**' or how many layers it should have