Applying Deep Learning to Aerospace and Building System Applications at UTC

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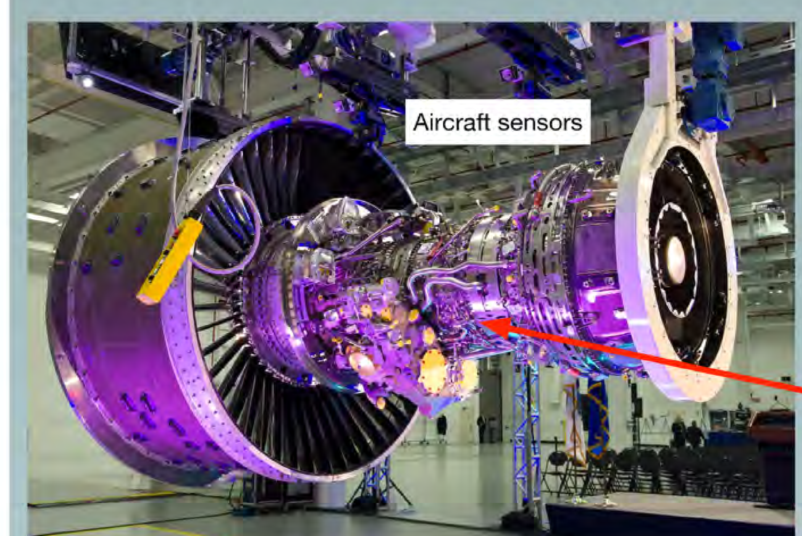
Introduction

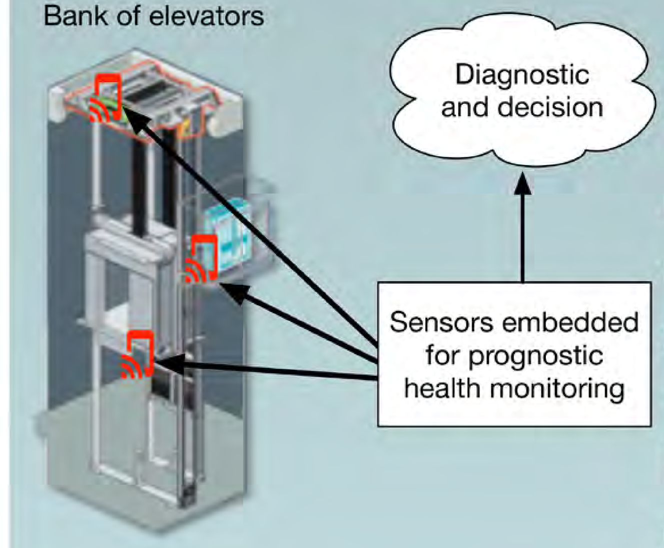
- Deep Learning is an evolving area of research in neural networks and it has been adopted by UTC for tackling various problems in aerospace and building systems.
- Three different use cases discussed here: (1) Aircraft sensor diagnostics for UTAS, Pratt & Whitney, (2) Prognostic Health Monitoring for Otis Elevators, (3) Chiller power estimation for Carrier Climate Control systems
- Aircraft sensors provide huge amount of data that needs to be tracked such as air data systems, fuel measurement and management systems, health and usage systems and mission data recorders.



Integrated sensor management and real-time analysis for variety of sensing suites for aircraft engines

On-board sensor diagnostics and data collection (FAST box) e.g. fuel measurement and management systems, mission data recorders, etc.

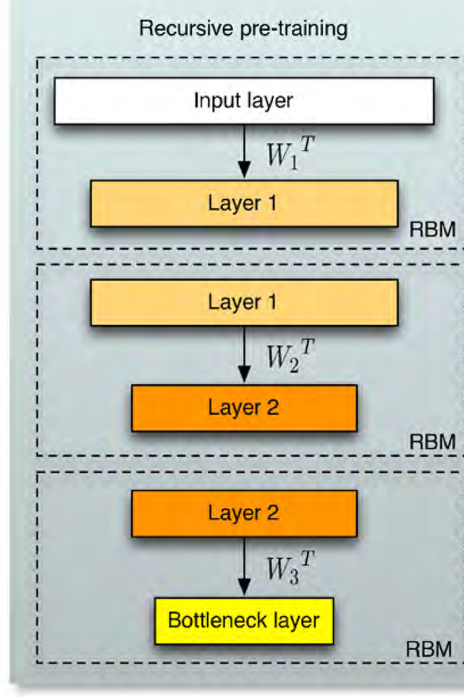
Bank of elevators



- Sensors embedded in Otis Elevator systems mainly used for collecting data about the health of the system
- Chillers used with Carrier HVAC units - understanding energy requirements

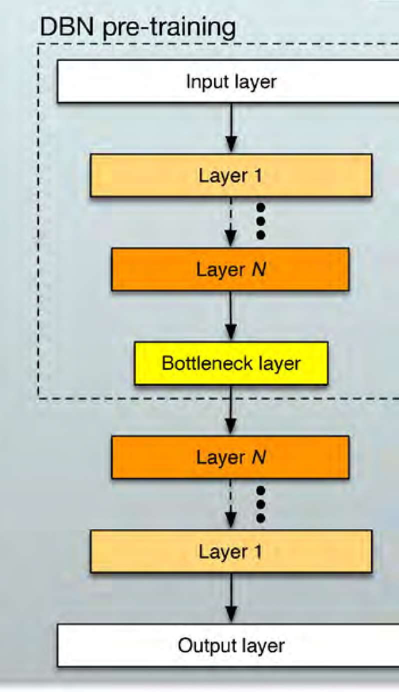
Carrier Chillers in HVAC units- understanding more about optimizing the energy utilization

Deep Belief Nets



- Deep Belief Nets (DBN) consist of using a probabilistic Restricted Boltzmann Machine (RBM) approach, trying to reconstruct noisy inputs.
- Training involves the reconstruction of a clean sensor input from a partially destroyed/missing sensor.
- Depending on the application, a final layer can be added after the bottleneck layer.

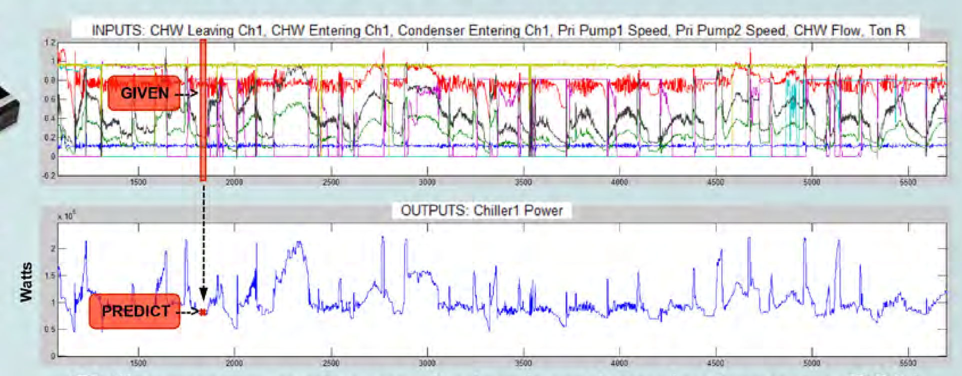
Deep Auto-Encoders



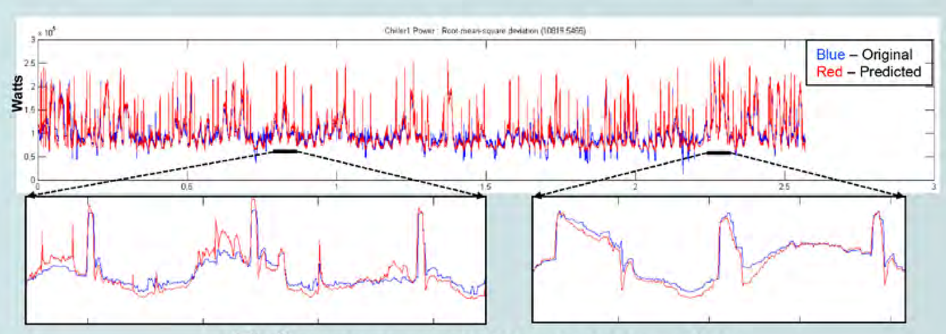
- Deep Auto-Encoders (DAE) performs the fine-tuning by generating the layers mirroring the initial network upto the bottleneck layer after the pre-training using the DBNs.
- The weights and the bias of the upper and lower hidden layers for the DAE are updated in the fine-tuning stage.
- The main objective of the DAE is to minimize the reconstruction error.

Implementation and Results

- 4xNvidia K40 GPUs with with 2880 cores and 12 GB device RAM each in Ubuntu OS workstation
- Theano based toolchain for Deep Learning
- Nvidia K40 with 12 GB device RAM - driving factor for large dataset inhalation, caching and computation - especially the pre-training stage for DBNs



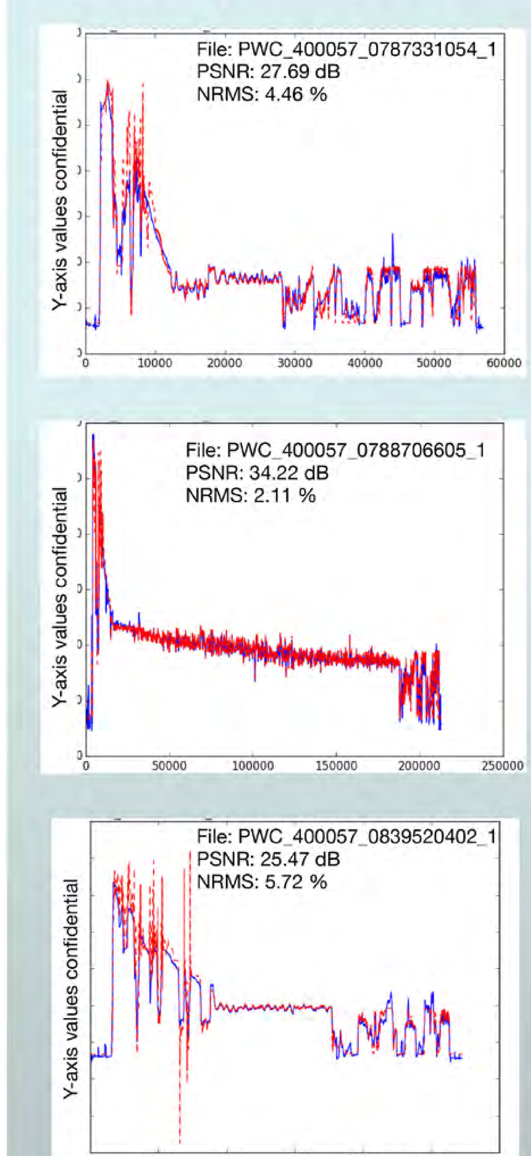
Chiller power output prediction based on the inputs to DBN



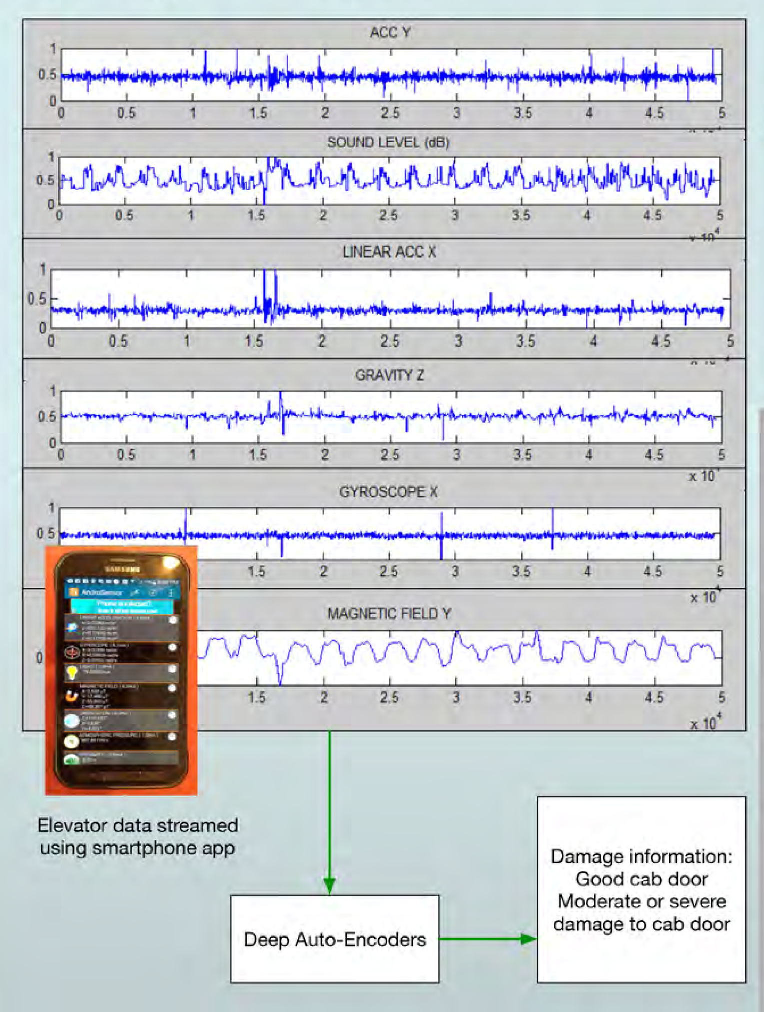
Chiller power output reconstruction

Algorithm	Reconstruction error
Discrete Bayesian Network	17192.63
Continuous Bayesian Network	17966.18
Structured Learning	14921.63
Koopman	16823
Deep Learning	10819.55

- Benchmarked Carrier Chiller energy utilization using variety of Machine Learning algorithms.
- Deep Learning approach provided the lowest reconstruction error enhancing the energy prediction capability.



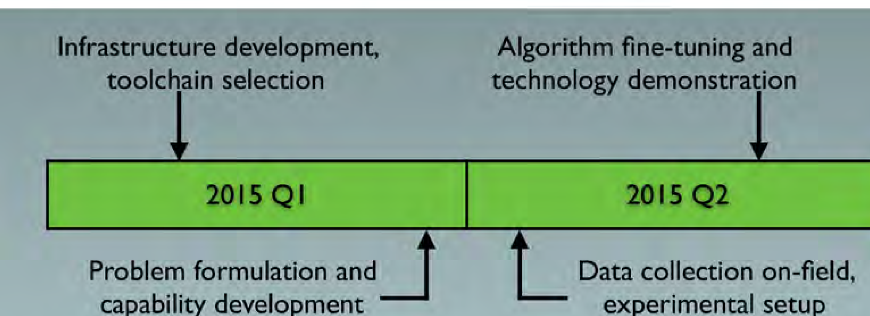
Sensor estimation from the FAST box



- Sensors embedded in the elevators streamed using smartphone app and then fed to the Deep Auto-Encoder.
- Performance metric measured in terms of the health of the elevator cab door

Conclusion

- Successful adoption of Deep Learning methodologies to UTC applications in aerospace and building systems as shown in the timeline.



Timeline of Deep Learning adoption and application to UTC

- Variety of use cases - sensor estimation from onboard sensing suites on aircraft engines using DBN, chiller power prediction for building systems using DBN, PHM in elevator systems using DAE.
- Huge amount of data generated - offline training using Nvidia GPUs.
- Online diagnostics and decision using Nvidia's Jetson GPUs - future.

References

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