A Hybrid Scheme for Fault Diagnosis with Partially Labeled Sets of Observations

EECOMOBILITY (ORF) & HEVPD&D CREATE

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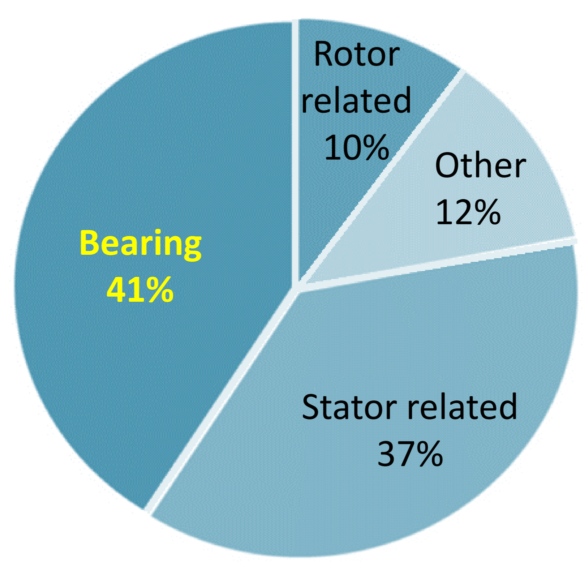
Bearing Defects

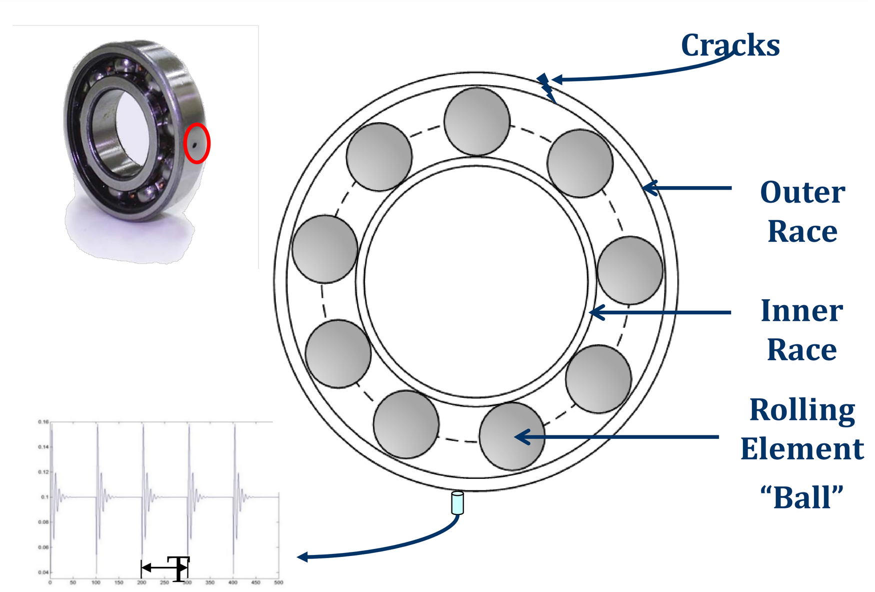
The undeniable importance of induction motors (IMs) in the industry including electric vehicles resulted in a large number of research works in various domains. Among the various failures in induction motors, almost 41% of them are caused by bearing defects. Such defects are followed by many consequences such as costly repairs, system breakdown, and in the worst case, workers injuries. Thus, finding a reliable and robust fault diagnosis system is of predominant concern, to ensure the reliable operations of the IMs.

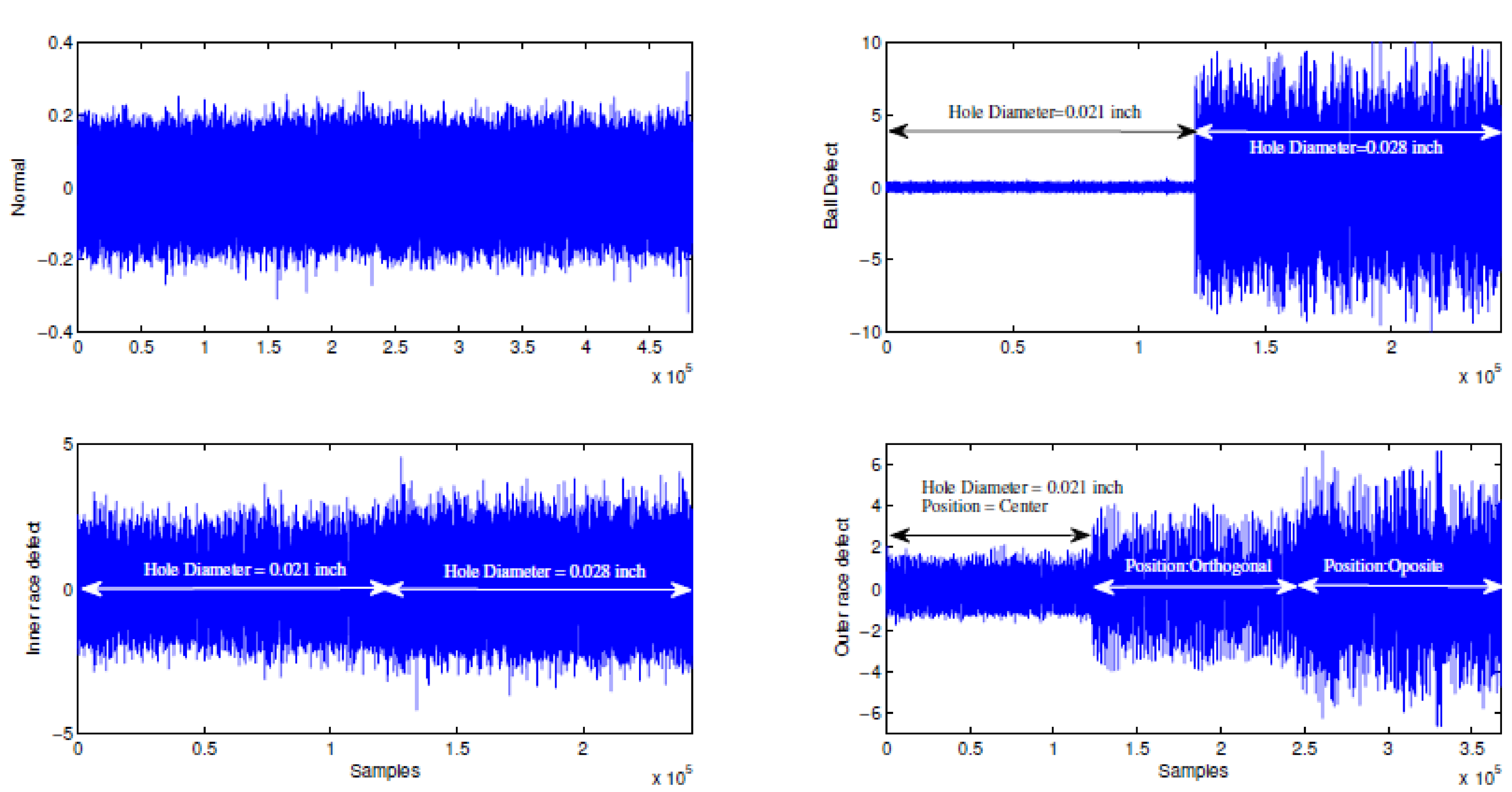


Signal Data

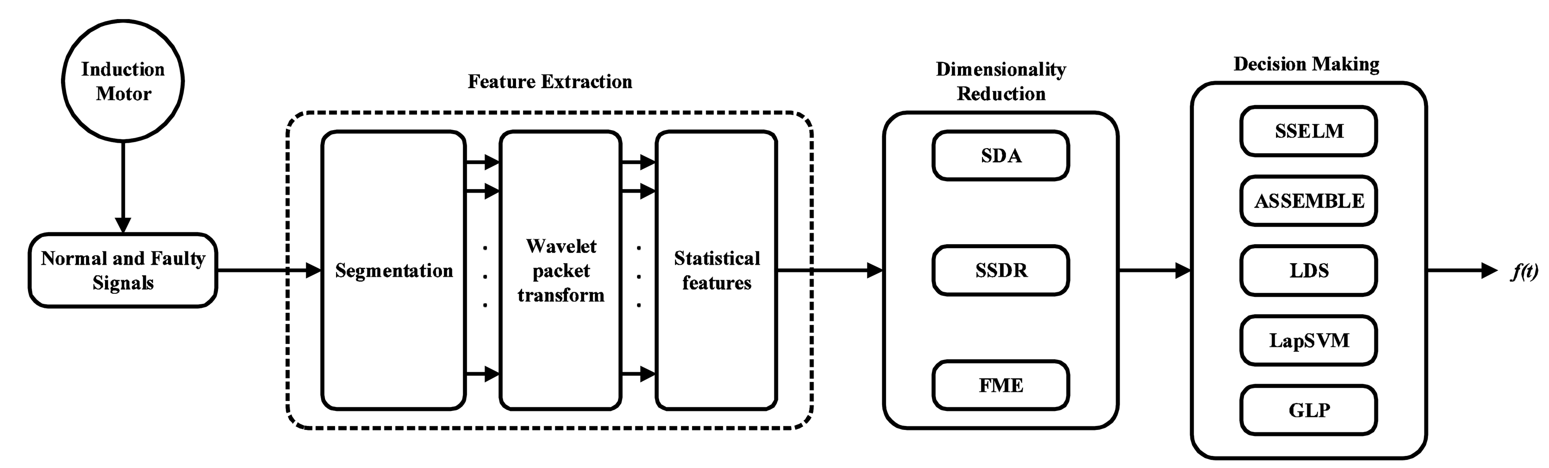
The Case Western Reserve University (CWRU) data represents vibration signals generated by different defects. These vibration signals are raw and contains noise and high-frequency components, which complicate the diagnostic process.

In this case study, bearing defects are categorized into four different types namely as normal, inner, ball, and outer race defects. Moreover, only five percent of the training data is labeled and the rest is unlabeled.



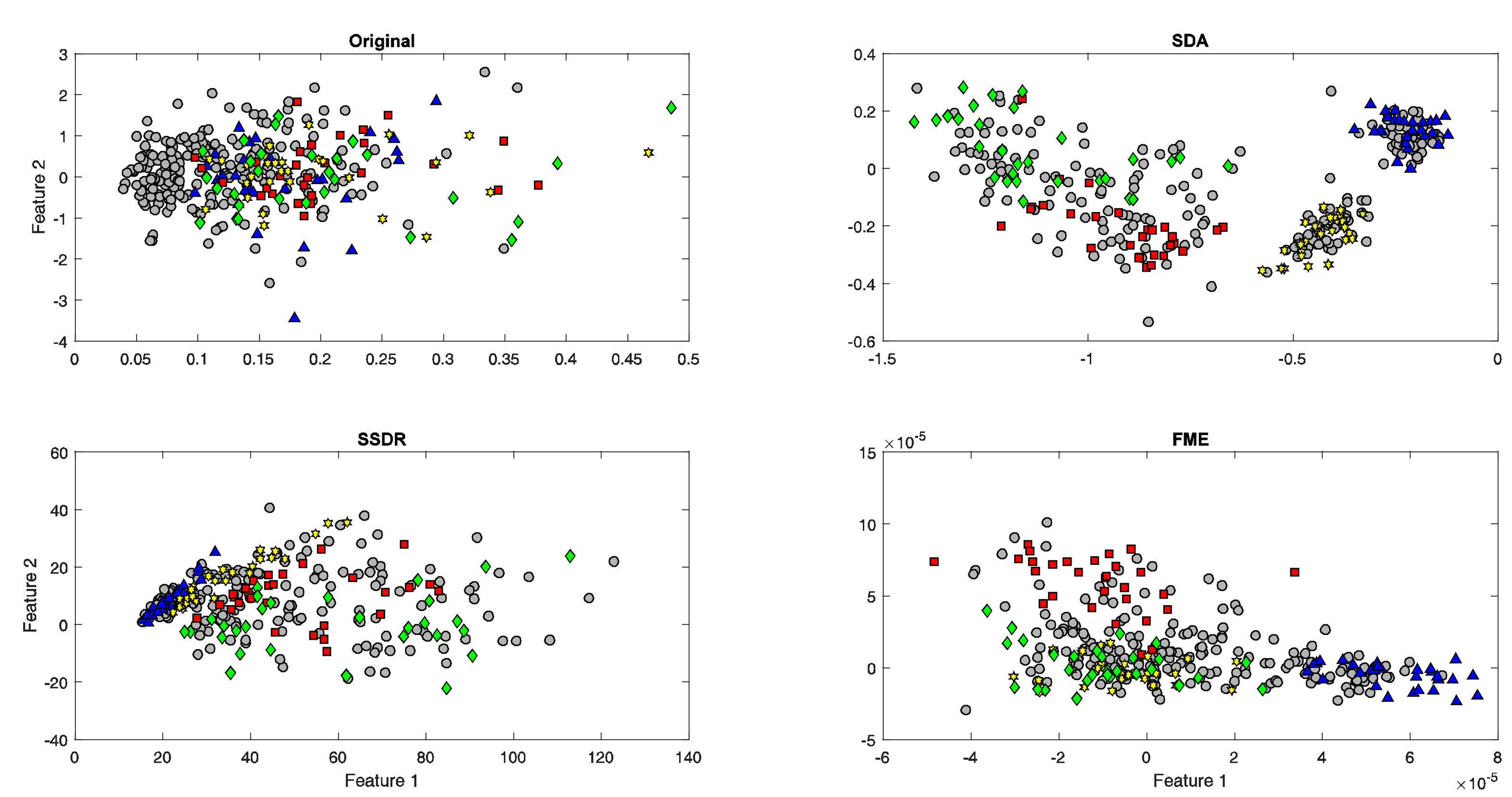


Hybrid Diagnostic Framework



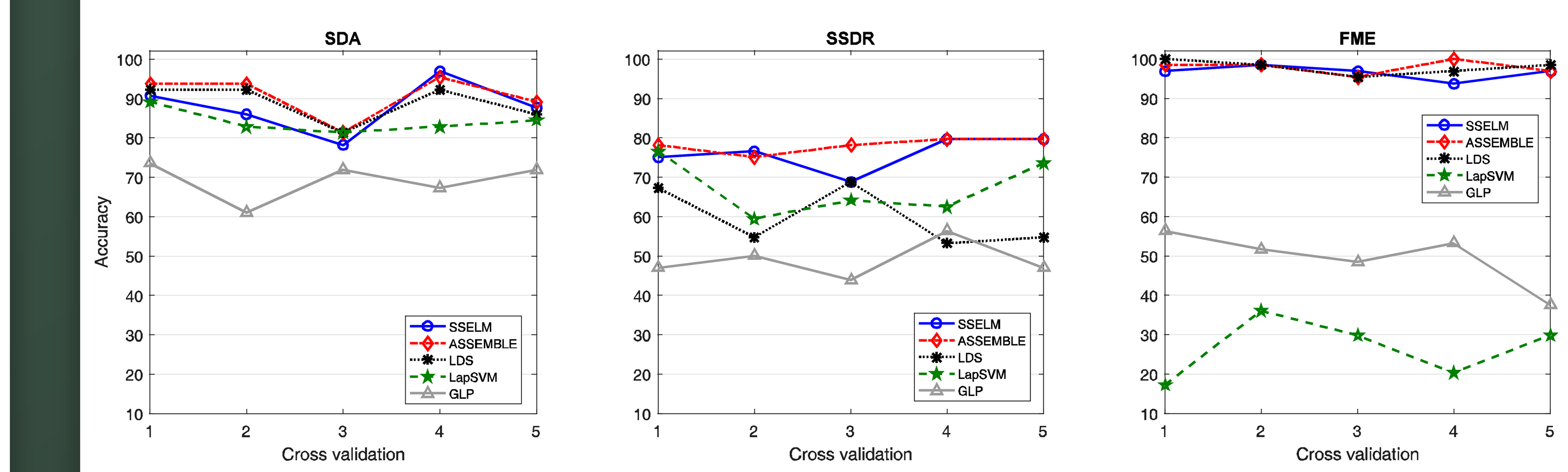
This diagnostic system contains three modules for feature extraction, dimensionality reduction and decision making. The feature extraction module is a three-steps process. This module initially segments the vibration signal into various non-overlapping partitions and, then, passes them through the WPT. It decomposes each segment into 16 different equal size packs with default frequency sub-bands as results of four levels of decomposition. Finally, seven different statistical features including Root mean square, Skewness, Kurtosis, Maximum, Minimum, Peak to peak and Variance of each pack are extracted (i.e., $16 \times 7 = 112$ features). Then, the 112 processed features are fed to the next module, dimensionality reduction, which provides the proper sets of small size features for the decision making module.

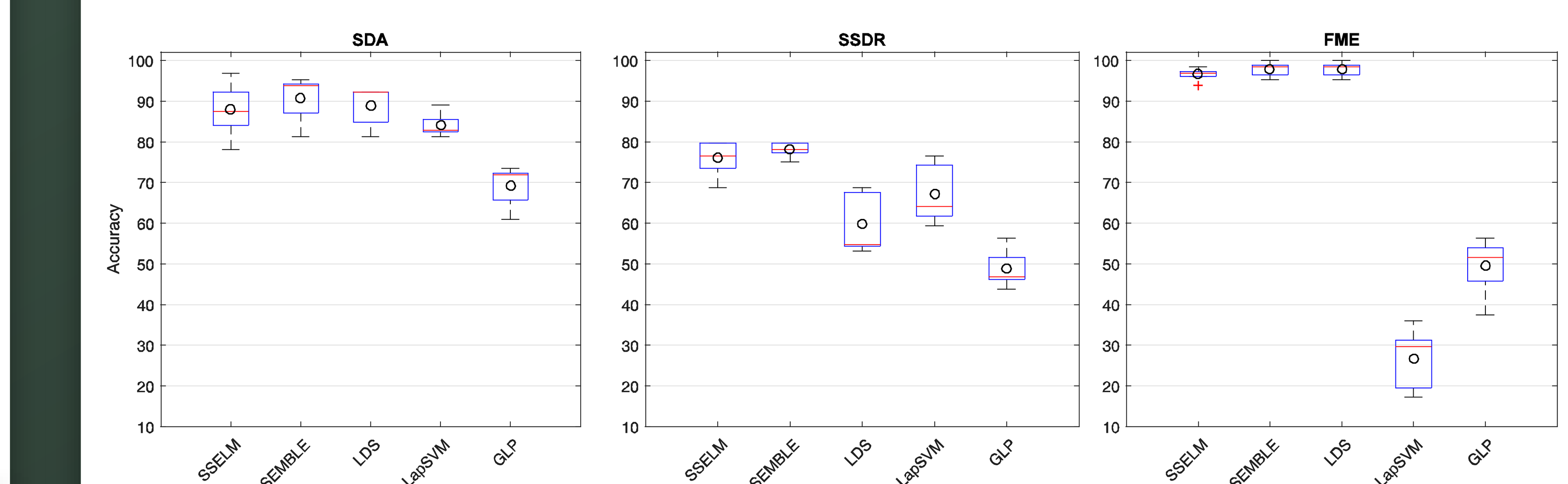
Semi-supervised Dimensionality Reduction

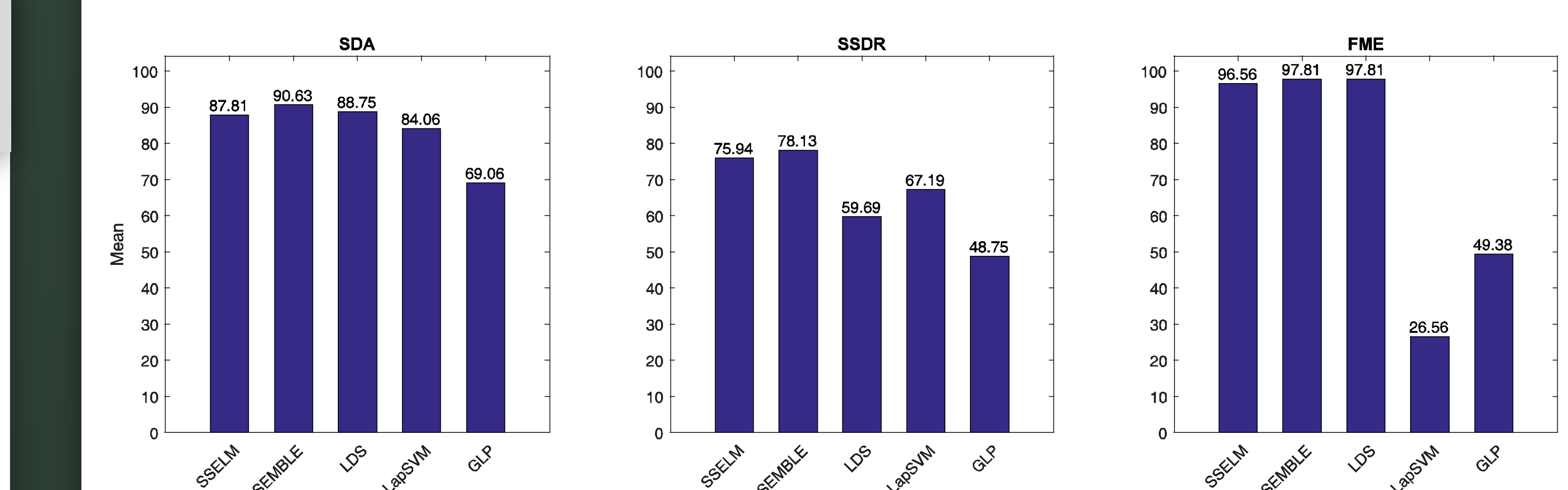


To diagnose bearing defects, vibration signals are preprocessed by three well-known dimensionality reduction techniques such as Semi-supervised Discriminant Analysis (SDA), Semi-Supervised Dimensionality Reduction (SSDR), and Flexible Manifold Embedding (FME).

Experimental Results







The choice of the best dimensionality reduction method for extracting features is FME since it is followed by high stability and performance through all experiments. Notice that one may choose the SDA method to create and reduce features, where fault classification is as a binary problem. This is mostly the case in fault detection problems where the goal is to distinguish faulty state from normal state. Nevertheless, the aim of this work is to go beyond that point and perform fault classification, which is a multiclass problem and requires multiclass fault classifiers.

Given the fact that the FME is chosen for the dimensionality reduction module, the best fault classifier should be picked among SSELM, ASSEMBLE, and LDS as they achieve the maximum accuracies using the features generated by FME. SSELM and ASSEMBLE are almost equally stable and accurate on FME output. However, considering the fact that ASSEMBLE is more stable and accurate w.r.t. other dimensionality reduction techniques, it is safe to say that ASSEMBLE is a more robust fault classifier. Furthermore, the ability to change the base learner in the ASSEMBLE makes it even a more flexible choice for different types of data distribution.

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Ontario Research Fund

We acknowledge the support of the Ontario Research Fund: Research Excellence Program.

NSERC CRSNG

We acknowledge the support of the Natural Sciences and Engineering Council of Canada (NSERC), which invests annually over $1 billion in people, discovery and innovation.