SELF-TUNING LINEAR ADAPTIVE GENETIC ALGORITHM FOR FEATURE SELECTION IN MACHINERY FAULT DIAGNOSIS

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ABSTRACT

Advanced pattern recognition of a machine learning classifier function, aka the black box allows automated machinery fault diagnosis and outperforms classic decision-making mechanisms. Nonetheless, the black box supervised learning is subject to overfitting when the usefulness of statistical input features is unknown, and results in biased prediction. An established genetic algorithm (GA) feature selection (FS) iteratively searches and extracts quality feature subset as the classifier input targeting fitness function prediction error minimisation. However, static genetic parameters are prone to premature convergence in multi-objective optimisation, while manual parameter tuning is computationally expensive. Thus, this study proposed an optimisation methodology based on adaptive search space strategy with a customised parameter tuning mechanism and stopping criteria revision to improve local convergence and prediction efficacy. By embedding an exploration-exploitation cycle as a function of the iterative fitness, Self-Tuning Linear Adaptive GA (Stella GA) adjusts the standard genetic parameters in parallel. Assuming convergence is detected via unique static fitness evaluation threshold, linear-additive-gain-increment-control equations gradually increase mutation rate and population size in an attempt to enhance population diversity. Alternatively, conservative genetic setting is initiated upon the global best score update to exploit the new search space neighbourhood. Stella GA alters parameters recursively until the hybrid stopping criteria is met to allow the tracking of floating genetic variables in preventing premature termination and computation explosion. As demonstrated in multi-objective optimisation problem with five machinery fault diagnosis benchmarking datasets, Stella GA generated feature subset candidate population capable of deterring premature convergence. A prediction benchmarking against modern classifiers (Deep Learning) and classic FS alternatives (GA, Binary Particle Swarm Optimisation and Neighbourhood Component Analysis) indicates the proposed Stella GA consistently returned classifier with desirable efficacy in accuracy (maximum 4.5% increment in hydraulic system) and confusion matrix statistical indicators (maximum 0.0974 increment in Matthews Correlation Coefficient for pumps), with the optimal feature reduction (maximum 58.59% in rotor fault diagnosis). This result suggests that Stella GA yielded optimal machinery fault diagnosis by further decrement in model overfitting, and the removal of manual tuning and unstable parameter feedback.

ABSTRAK

Pengelasan corak hasil dari fungsi pembelajaran mesin berciri kotak hitam membolehkan diagnosis kesalahan mesin secara automatik dan mengalahkan mekanisme klasik dalam membuat keputusan. Tetapi, kualiti ciri input statistik belum dikenalpasti dalam pembelajaran berselia yang bersifat kotak hitam, dan menyebabkan masalah berlebihan. Algoritma genetik (GA) merupakan satu kaedah pemilihan ciri (FS) berfungsi memeriksa dan mengekstrak ciri input subset berdasarkan kualiti secara rekursif untuk tujuan pengurangan kesalahan ramalan. Namun, tetapan parameter GA yang statik mudah terdedah kepada penumpuan lokal, manakala melaraskan parameter secara manual memerlukan kos komputasi yang tinggi. Jesteru, penyelidikan ini memperkenalkan cara pengoptimuman baharu mengenai strategi mencari ruang secara adaptif dengan mekanisme penyelarasan khas untuk paramater genetik bersama dengan penyemakan kriteria untuk berhenti, supaya memperbaiki penumpuan lokal dan pencapaian ramalan. GA secara penyesuaian diri dan linear adaptif (Stella GA) mengubah nilai parameter secara selari dengan melampirkan kitaran explorasi-eksploitasi sebagai fungsi pencapaian kecergasan. Kitaran explorasi-eksploitasi menerimapakai persamaan linear penambah gandaan kawalan bagi menambahbaikan kepelbagaian populasi dengan melaras kadar mutasi dan saiz populasi jika penumpuan lokal dikesan dengan ambang unik untuk penilaian kecergasan yang statik. Tetapan konservatif diaktifkan ketika skor terbaik dikemaskini untuk mengekspoitasi ruang carian terbaru. Stella GA meminda parameter secara rekursif sehingga memenuhi kriteria untuk berhenti untuk memastikan parameter dalam lingkungan supaya penamatan pramatang dan peningkatan computasi yang mendadak dielakkan. Seperti yang diperlihat dengan lima set penanda aras diagnosis kesalahan mesin dalam masalah pengoptimuman pelbagai objektif, Stella GA menjana calon populasi ciri subset yang mampu membendung penumpuan pramatang. Dibandingkan dengan pelbagai pengelasan moden dan FS klasik, Stella GA menjana keberkesanan dalam ramalan yang paling kosisten, dalam ketepatan (maksimum kenaikan 4.5% dengan sistem hidraulik), petunjuk statistik matriks kekeliruan (maksimum kenaikan 0.0974 dalam pekali korelasi Matthews dengan pam) dan pengurangan ciri di tahap optimum (maksimum 58.59% dengan diagnosis kesalahan di pemutar). Keputusan menunjukkan Stella GA menghasilkan ramalan optimum dengan pengurangan masalah berlebihan, penyingkiran penyelarasan manual dan maklumbalas parameter yang tidak stabil.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AC	-	Alternating Current
AE	-	Acoustic Emission
AFSA	-	Artificial Fish-Swarm Algorithm
AGA	-	Adaptive Genetic Algorithm
AI	-	Artificial Intelligence
ANFIS	-	Adaptive Neuro-Fuzzy Interference System
ANN	-	Artificial Neural Network
AOEA	-	Adaptive Operators Evolutionary Algorithm
ARX	-	Autoregressive with exogenous terms
BPSO	-	Binary Particle Swarm Optimisation
CBFO	-	Chaotic Bacterial Foraging Optimisation
CE	-	Cooling Efficieny in %
CF	-	Crest Factor
CH	-	Choromosome
CNN	-	Convolution Neural Network
$con\ iter$	-	Converged generation count
$con\ max$	-	Convergence generation limit
COVAL	-	Covariance-Alignment
CP	-	Cooling Power in kW
cpm	-	Measurement Frequency in Hz
CPU	-	Central Processing Unit
dB	-	Decibel
DCGA	-	Dynamic Crossover GA
dir	-	Filter type of the measurement and direction in Unit
$Dist$	-	Minimum gap between best score and average population score
DL	-	Deep Learning
e	-	Normalised noise

EALasso	-	Extended Adaptive Least absolute shrinkage and selection operator
EMD	-	Empirical Model Decomposition
EOL	-	End-of-Life
EPS	-	Motor power in W
ER	-	Error rate
FEA	-	Finite Element Analysis
FFT	-	Fast Fourier Transform
FN	-	False Negative
FP	-	False Positive
FPR	-	False Positive Rate
FS	-	Volume flow in l/min
FSCBAS	-	Feature Selection based Clustering Binary Ant System
GA	-	Genetic Algorithm
$gain$	-	Exploration parameter
ga_{iter}	-	Static candidate evaluation count
GB	-	Gigabyte
gen	-	PSO iterative location/GA iterative generation
$gen\ iter$	-	Maximum candidate evaluation convergence limit
GHz	-	Gigahertz
GP	-	Genetic Programming
IDE	-	Integrated Development Environment
IF	-	Impulse Factor
IFL	-	Intuitionistic Fuzzy Logic
k-NN	-	k-Nearest Neighbor
$kfoldLoss$	-	Ten-fold cross-validation loss function
kr	-	Kurtosis
kW	-	kiloWatt
LGDNN	-	Local-Global Deep Neural Network

LSTM	-	Long Short-Term Memory
Matlab	-	Matrix Laboratory
$max\ mu$	-	Maximum mutation rate
$max\ pop$	-	Maximum population size
MCC	-	Matthew Correlation Coefficient
MED	-	Minimum Entropy Deconvolution
MIMO	-	Multiple Input Multiple Output
mis	-	Measurement in Unit
$misr$	-	Earlier Measurement in Unit
MF	-	Margin Factor
MFS-RDS	-	Machinery fault and rotor dynamics simulator
ML	-	Machine Learning
MOD FA	-	Modified Firefly Algorithm
MpGA	-	Multi-population GA
mu	-	GA mutation rate
NCA	-	Neighborhood Component Analysis
NDE	-	Non-Destructive Evaluation
N_{LBL}	-	Total Negative Label
Nm	-	Motor Torque
NoC	-	Network on Convolutional
OEM	-	Original Equipment Manufacturer
$omega$	-	Machine Speed in RPM
$opt\ gen$	-	Maximum generation number
OVA	-	One-Versus-All
OVO	-	One-Versus-One
PCA	-	Principal Component Analysis
P_{LBL}	-	Total Positive Label
$pop\ size$	-	Population Size
PRBM	-	Priority Rule-Based Method

PS	-	Pressure in Bar
PSO	-	Particle Swarm Optimisation
RBF	-	Radial Basis Function
Ref	-	Reference point
ReLU	-	Rectified Linear Unit
RMS	-	Root Mean Square
RNN	-	Recurrent Neural Network
RPM	-	Revolutions per minute
SAGA	-	Self-Adaptive Genetic Algorithm
SALS	-	Self-Adaptive Local Search
Set	-	Data superset
SI	-	Swarm Intelligence
si	-	Particle/Swarm candidate
SCADA	-	Supervisory Control and Data Acquisition
SCGA	-	Self-Configuring Genetic Algorithm
SE	-	Efficiency factor in %
SF	-	Shape Factor
Sk	-	Skewness
SNR	-	Signal-to-Noise Ratio
Stella	-	Self-Tuning Linear Adaptive
sup	-	Machine Support
SVM	-	Support Vector Machine
$threshold$	-	Candidate evaluation convergence limit
TN	-	True Negative
TP	-	True Positive
$trainlm$	-	Levenberg-Marquart training function
$trainscg$	-	Scale Conjugate Gradient training function
TS	-	Temperature in °C
VC	-	Variable contribution

VMD	-	Variational Model Decomposition
VS	-	Vibration in mm/s
WOA	-	Whale Optimisation Algorithm

LIST OF SYMBOLS

t	-	Time sampling
N	-	Total vector elements
W_{sin}	-	Sine wave
f_c	-	Frequency component
ψ	-	Mother Wavelet
b_{ψ}	-	Wavelet window translation
a_{ψ}	-	Wavelet window scale factor
x	-	Input vector
K	-	Arbitrary total target label number
y	-	Output vector
$\hat{y}$	-	Predicted output vector
$\in$	-	Is member of
$\mathbb{R}$	-	Set of real numbers
$feat$	-	Arbitrary total input features
$feat_{GA}$	-	Genetic Algorithm input feature subset
$\subset$	-	Proper subset of
$func$	-	Function
ε	-	Prediction error
w	-	Neuron weight
n_i	-	Input neuron
n_h	-	Hidden neuron
h	-	Hidden layer
n_o	-	Output neuron
X	-	Input matrix
C	-	LSTM feature elements
S	-	Number of LSTM time steps
h_t	-	LSTM hidden state

c_t	-	LSTM cell state
D	-	LSTM hidden neuron
f	-	LSTM forget gate component
i	-	LSTM input gate component
o	-	LSTM output gate component
g	-	LSTM cell candidate
σ_c	-	LSTM tanh function gate activation
σ_g	-	LSTM sigmoid function gate activation
$\odot$	-	Hadamard product
b	-	Bias
k	-	Neighborhood component number
L^2	-	Euclidean metric cost function
W	-	SVM coefficient vector
ξ	-	Slack variable
L	-	Lagrangian dual optimisation
α	-	SVM weighting coefficient
Φ	-	Kernel function
γ	-	Kernel hyperparameter
d_w	-	Distance
w_r	-	Feature weightage
P	-	Selection probability
r	-	Feature instance
z	-	NCA feature space margin
σ	-	NCA kernel width
j	-	NCA selection point
P_t	-	Average NCA leave-one-out probability
λ	-	NCA regulating variable
I	-	Identical function
l	-	Loss function

$Func(w)$	-	NCA regularised objective function
P_{si}	-	PSO personal best position
P_{best}	-	PSO global best position
x_{si}	-	Particle coordinate vector
v_{si}	-	Particle velocity vector
c_1	-	PSO cognitive acceleration constant
c_2	-	PSO social acceleration constant
R_1, R_2	-	PSO diagonal, stochastic variable matrix
Ω	-	PSO Inertia weight
m	-	Index number for particle coordinate vector
μ	-	PSO stochastic variable
U	-	Random uniform distribution
g_{iter}	-	GA iterative best classification score
g_{best}	-	GA global best classification score
m^3/s	-	Volumetric flow rate
Δp	-	Pressure differential
θ	-	Model estimated parameters
ω	-	Rotational speed
Q	-	Pipe discharge flow
M_{motor}	-	Motor Torque
r_1, r_2, r_3, r_4	-	Residual
$\bar{x}$	-	Mean value
σ	-	Standard Deviation
x_{max}	-	Maximum amplitude
σ^2	-	Variance
1-norm	-	Summation of absolute vector element
σ_e^2	-	Noise variance
Z	-	White zero mean gaussian noise sequence
$\mathcal{N}$	-	Normal Distribution

ζ	-	Additive coloured noise instance
S_N	-	Additive coloured noise sequence
ν	-	Operating frequency
T_s	-	Sampling rate
$<$	-	Logical less than operator
$>$	-	Logical greater than operator
$\wedge$	-	Logical and operator
$\vee$	-	Logical or operator
$\Longleftrightarrow$	-	Logical equivalent operator
R_T^2	-	Coefficient of Determination

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

Fault diagnosis is the process involving the continuous monitoring of degrading machines to observe and detect various types of errors and their exact location. Fault diagnosis is conducted by subjecting machinery operating signals from sensors to statistical analysis in order to analytically determine behaviour changes via digitised equipment or visual inspection. During the lifespan of a machine, fault diagnosis is pivotal in providing a health status overview and knowledge of fault severity, if any, to determine whether condition-based maintenance is required. Typical condition-based maintenance classes include periodic, preventive, and predictive types, which are accompanied by a series of corrective measures if necessary. In the 2016 annual U.S. census, maintenance and repair expenditure amounted to approximately US$ 50 billion. Consequently, predictive maintenance is deemed to be the most effective maintenance practice as it successfully reduces at least 15% of the total maintenance costs [1].

The latest trend in fault diagnosis adopts data mining techniques as a result of the advancement of digital signal processing and Internet of Things sensor instruments [2]. While it is estimated that 33 zetabytes of data volume were generated worldwide in 2018, this figure is predicted to swell in the future [3] (see Figure 1.1). Consequently, the management of the generation of big data involves a new level of sophistication in signal and pattern processing measures. To this end, machine learning (ML) algorithms are a domain of Artificial Intelligence (AI), which provide automated decision-making process that analyse and correlate dataset details with embedded training function. The training process develops and returns a classifier as a function of the input features consists of an algorithmic reasoning sequence. A pretrained classifier specialises in pattern recognition problem solving with better prediction accuracy than that of general practice.

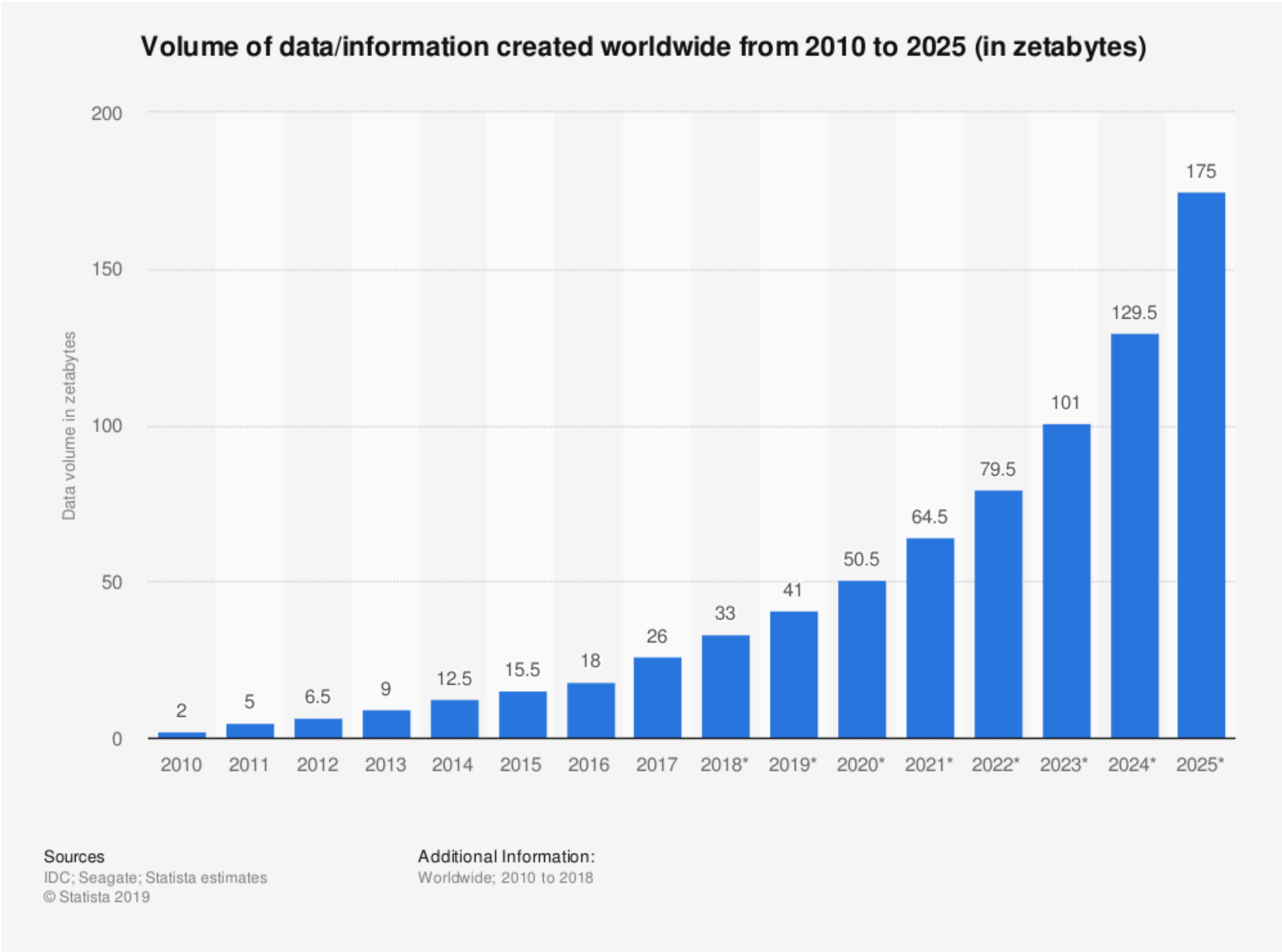

Figure 1.1 Annual size of data files produced globally

The integration of AI data mining in predictive maintenance is projected to experience a significant increase over the next five years, from 28% to 66%, due to attractive financial returns in industry applications [4]. Profitability in the form of asset productivity is expected to increase as much as 20%, while maintenance costs and manufacturing detraction rate are capable of further reductions of 10% and 30%, respectively.

Sufficient reports acknowledge the convenience of AI in fault diagnosis with regard to economic efficiency. In response to the need for automated fault diagnosis in the field of predictive maintenance, the development of robust and futuristic classifiers by means of algorithmic technology is currently of research interest. In this regard, ongoing studies have focused in many ways on classifier optimisation to tackle existing bias and overfitting complications that hinder the prediction performance.

1.2 Problem Statement

For the application of fault diagnosis, the operating signals are useful information in indicating the targeted machine conditions numerically. To establish the mathematical relationship between the input (sensor signals) and output (machine status), the function of ML is to generate a unique classifier via input-output dataset training process. ML algorithms are favourable due to their ability to recognise complex, hidden statistical patterns which are beyond the grasp of visual inspection or conventional methods. Nonetheless, in the event of the unknown quality of input features when a *priori* knowledge is absent, ML black box training easily lead to unwanted overfitting. In particular, overfitting is mainly induced by the overdesigning of the classifier structure, along with the undermining of noisy signals [5].

To address the drawbacks caused by overfitting, feature selection (FS) is carried out to elect a representative input subset combination from a superset consisting of common statistical signatures. Current FS evaluation tasks can be categorised into filter, wrapper, and embedded functions. In this regard, genetic algorithm (GA) is a heuristic optimisation technique inspired by Darwin's theory of evolution. Typically, GA employs three types of genetic operators in creating an iterative candidate population that targets global optima for the desired fitness function, until a pre-defined stopping criteria is met. The GA feature selection criteria are generally reflected in fitness function as the relevancy of the feature input subset to the prediction performance.

Nonetheless, GA has the tendency to encounter local convergence in a multiple local optima situation, in particular of machinery fault diagnosis applications, where the global optima is unknown. Investigations has suggested that the premature convergence that occurs in GA is likely to be due to stationary genetic operators settings. Identical genetic parameters over simulation time are expected to be inadequate to adapting to the need for search space exploration and exploitation, given both circumstances are equally important in global optima probing [6]. Furthermore, preset stopping criteria overlook the optimisation development in the form of iterative fitness value update is vulnerable to premature termination and computation explosion.

As optimisation is problem-dependent, general parameter guidelines are not applicable to unique machinery fault diagnosis conditions. Exercising manual parameter tuning is not only tedious, but also computationally demanding given there is an exponential increase in possible combinations of genetic variables [7]. The effectiveness of trial-and-error parameter tuning for better classifier performance is uncertain. On top of an unlikely global best solution and nonexistent universal GA parameter setting, feature selection is further complicated by a non-trivial trade-off between genetic information tracking and computation effort. High mutation rate is required for large population fitness evaluation to reduce overdependent on elitism which is considered redundant with repetitive, identical candidates. Vice versa, overreliance on a mutation event leads to information loss.

Accordingly, extensive research on a parameter tuning mechanism corresponding to classifier optimisation has been implemented in an effort to avoid undesirable premature convergence. Nevertheless, a complete adaptive tuning package covering the essential aspects from the genetic operators settings to revision of the stopping criteria is visibly lacking. This negligence eventually places the stability of the parameter tuning model at risk, and subsequently returns a suboptimal machinery fault diagnosis solution.

1.3 Research Questions

As a summary from problem statement, numerous challenges on the current ML fault diagnosis related technology development remain. The list of queries is outlined in sequential order, as follows:

1. Uncertain input feature quality presents an overcomplex prediction pattern, noted as the overfitting, and affects decision making in the overdesigned classifiers. What action could be able to measure feature quality and improve underperformance as a whole?
2. The rigid searching approach provided by a constant parameter setting in classic GA is susceptible of unwanted local convergence. Without laborious manual tuning, what are the alternatives to revise genetic parameters, regardless of classifier selection as fitness function?
3. An additional computation is required to perform parameter tuning. How to modify interrelated GA variables without premature termination or computation explosion since trade-off between computation cost and genetic information tracking is inevitable?
4. FS is a multi-objective optimisation problem involves choosing a subset of input in the interest of prediction efficacy. How to interpret multi-objective analytical performance changes yield from an adaptive parameter mechanism embedded GA compare to existing FS methods?
5. With the aim to reduce model overfitting due to static GA parameter generated local convergence, what is the significant take away from current wrapper-based FS parameter tuning research?

1.4 Objectives of the Study

The following describes the objective of research, aligned to the questions:

1. To develop a novel FS methodology for minimising feature quality-induced overfitting. The effectiveness of overfitting reduction in feature subset trained classifier is numerically express as prediction error decrement with over 16.6% feature reduction percentage.
2. To design an adaptive parameter tuning mechanism as a function of iterative fitness feedback in replace of static genetic parameters, with the aim to detect and overcome local convergence. The proposed GA method capable of deploy feasible global optima searching strategy which is absent in classic GA.
3. To embed an iterative search space exploration-exploitation cycle and stopping criteria revision for interrelated genetic parameter tuning and monitoring while prevent computation explosion and loss in information tracking.
4. To improve general purpose ML fault diagnosis regardless of classifiers using adaptive version of GA. The proposed GA FS is benchmark against existing FS and end-to-end ML package to identify optimal classifier which return minimum prediction error in four repository datasets and laboratory controlled experiment.

1.5 Scope of the Study

This subsection defines the coverage of current research to deliver a significant outcome. The scope is arranged in the sequence flow of analysis, from pinpoint targeted field, data acquisition, programming software development and implementation to result validation, as below:

1. The investigation focuses on machinery multiclass fault diagnosis applications to distinguish normal and abnormalities with continuous and discrete variables.

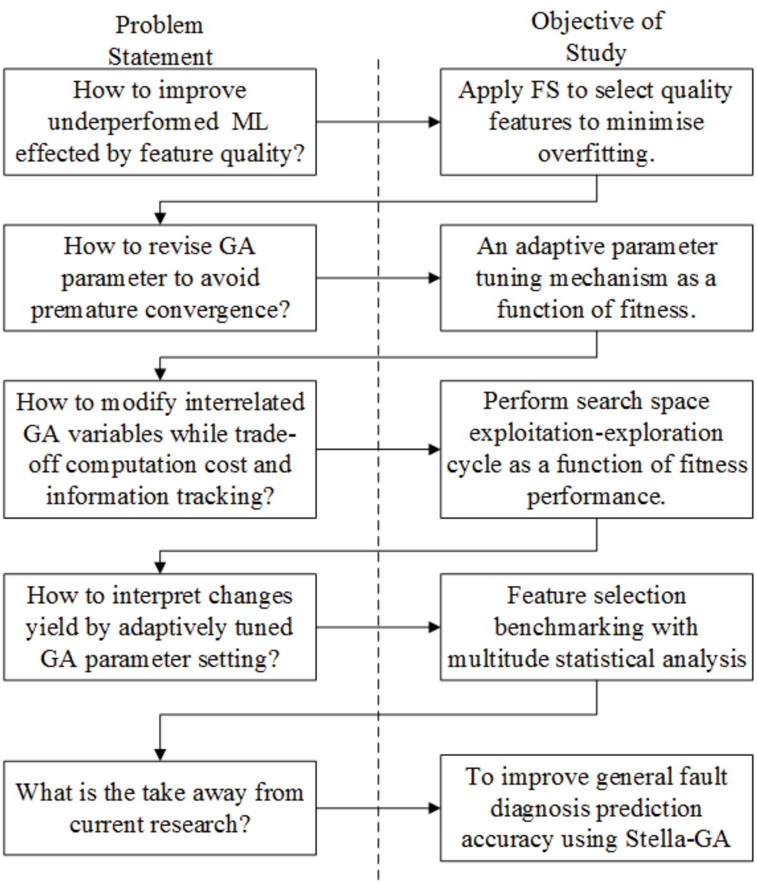

Figure 1.2 Problem Statement and Objective of Study

The contributions of related technology subfields are acknowledged and room for improvement is identified.

2. Data analysis involves common degraded conditions acquired from the integrated components of machines. Four repository datasets targeting hydraulic system, pumps, robots and centrifugal pumps as multiple input-multiple output tribological systems. Laboratory controlled experiment with SpectraQuest machinery fault simulator study the fault-induced dynamic behaviour under various speed and fault severity. Time domain signals are harvested in the form of vibration, current, temperature, speed, operating frequency, internal pressure, volume flow, and torque under distinctive health conditions. A list of proven statistical features extracted time series waveform in accordance to sensor locations and directions.

3. The programming algorithm conceptual design is developed in the Matrix Laboratory (Matlab) software integrated development environment (IDE). The

classifier options are classic ML algorithms ranging from Artificial Neural Network (ANN), k-Nearest Neighbors (k-NN), Support Vector Machine (SVM) and Deep Learning (DL) which have been proven to be useful as fitness function in data-driven prediction. Next, FS choose a feature subset with wrapper and filtering method to train classifiers.

4. FS benchmarking demonstrates the severity of overfitting effect and the effectiveness of a relevant feature subset. Numerous statistical analysis measures prediction outcome, confusion matrix statistical indications and feature reduction percentage to rigorously validate the efficacy of the feature subset trained classifiers. The feasibility of the proposed FS technique in overcoming local convergence is also observed and discussed in detail.

1.6 Thesis Outline

The outline of the study is divided into four sequential chapters:

1. First, a thorough review of recent relevant research is conducted. The literature review explicitly covers the fundamental workings and breakthrough of the feature selection technique, the novelty of available parameter tuning channels, as well as key points to take away. The research gap is identified during this stage.
2. Second, a comprehensive research methodology discusses the strategy used to implement and verify the proposed GA operating parameter self-tuning mechanism. In addition, a blueprints summary of the research methodology in the form of process flow is tabulated.
3. Third, the background of repository dataset and experimental studies in time domain is discussed, followed by corresponding evaluation results in detail. Extensive comparisons and the reasoning underlying the validation of the feature selection outcomes are emphasised under a consolidated conclusion.
4. Finally, the conclusion and recommendations for future work are presented specifically based on the complete findings.

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Appendix A Neighborhood Component Analysis: Pseudo code

Algorithm 1 Neighborhood Component Analysis in feature coefficient evaluation

Input: NCA operating parameters, training and testing datasets
Output: Feature weight coefficient, w

Initialisation : Load $w = \{1\}, \in \mathbb{R}^{feat}$, training and testing datasets
regularisation term λ tuning via cross-validation
select λ with the least classification loss
LOOP Process
for $Set\ t = 1$ to N **do**
  for $sample\ j = 1$ to $N \wedge t \neq j$ **do**
    distance, d_w between x_j and $Ref(x_t)$ (2.17)
    probability of x_j as reference x_t: $P_{tj}(w)$ (2.19)
    average leave-one-out probability, $P_t(w)$ (2.20)
    average leave-one-out probability of classification/regression accuracy, $Func(w)$
  end for
end for
for $Feature\ r = 1$ to $feat$ **do**
  for $Step$ 1 to $limit$ **do**
    loss function, $l(y_t, y_j)$ minimisation
    weight coefficient, $\hat{w}_r$ minimisation (2.22)
    $Func(\hat{w})$ maximisation (2.21)
    if $Func(\hat{w})_{Step} \iff Func(\hat{w})_{Step-1}$ **then**
      $w_r = \hat{w}_r$
    else
      $Step = Step + 1$
    end if
  end for
end for
return w

Appendix B Binary Particle Swarm Optimisation: Pseudo code

Algorithm 2 BPSO feature selection evaluation

Input: BPSO operating parameters, training and testing datasets
Output: Feature subset P_{best}

Initialisation : Load BPSO operating parameters (Table 3.11), training and testing datasets

LOOP Process

for $Location\ gen$ = 0 to $opt\ gen$ **do**
    for $Particle\ si$ = 1 to $pop\ size$ **do**
        Assign $particle$ position/binary sequence, $x_{si}(gen)$ (2.26)
        Classifier training with training dataset contains feature subset only
        Prediction and validation with testing dataset, $func(x_{si}(gen))$
        if $(func(x_{si}(gen))$ < (existing best classification score for si, $func(P_{si})) \lor (gen = 0)$ **then**
            update $P_{si} = x_{si}(gen)$
            if $(func(x_{si}(gen))$ < existing global best classification score, $func(P_{best})) \lor (gen = 0 \land si = 1)$ **then**
                update $P_{best} = x_{si}(gen)$
            end if
        end if
    end for
    Update $particle$ velocity, $v_{si}(gen+1)$ (2.27)
    Transform $v_{si}(gen+1)$ to $v'_{si}(gen+1)$ (2.28)
    Update $particle$ position/binary sequence, $x_{si}(gen+1)$ (2.29)
    Check stopping criteria:
    if $(gen \iff$ opt gen$) \lor (func(P_{best}) = 0)$ **then**
        $break$
    end if
end for
return $P_{best} \land$ stopping message

Appendix C Genetic Algorithm: Pseudo code

Algorithm 3 GA feature selection evaluation

Input: GA operating parameters, training and testing datasets
Output: Feature subset $feat_{GA}$

Initialisation : Load GA operating parameters (Table 3.10),
training and testing datasets
LOOP Process

for $Generation$ = 0 to $opt\ gen$ **do**
  for $candidate$ = 1 to $pop\ size$ **do**
    Classifier training with training dataset contains feature subset only
    prediction and validation with testing dataset, $func(feat_{GA})$
    if (iterative best classification score, g_{iter} < existing global best classification score, g_{best}) $\vee$ ($Generation = 0 \wedge candidate = 1$) **then**
      update $g_{best} = g_{iter}$, $func$, and $feat_{GA}$
    end if
  end for
  Check stopping criteria:
  if ($Generation \iff opt\ gen$) $\vee$ ($g_{best} \iff 0$) $\vee$ (Meeting maximum $Generation$ of converged fitness value) **then**
    $break$
  end if
end for
return $feat_{GA} \wedge$ stopping message

Appendix D Self-Tuning Linear Adaptive Genetic Algorithm: Pseudo code

Algorithm 4 Stella GA parameter tuning

Input: $Dist\ g_{best}$, $con\ iter$, $con\ max$, ga_{iter}, $threshold$, $gen\ iter \wedge opt\ gen$
Output: $Dist\ g_{best}$, $con\ iter$, $con\ max$, ga_{iter}, $threshold$, $gen\ iter \wedge opt\ gen$
Initialisation : Load Stella GA operating parameters (Table 3.10)
while Run Algorithm 3 **do**
Check convergence status for current $Generation$:
$Dist$ = current average Score - current Best Score
if ($Dist < Dist\ g_{best}$) **then**
  update $Dist\ g_{best} = Dist$, $opt\ gen$ + = 1, & $con\ iter$ + = 1
  if ($con\ iter \iff con\ max$) **then**
    Exceed allowable convergence generation limit: $break$
  end if
end if
Check fitness update:
if (iterative best score, g_{iter} < existing global best score, g_{best}) **then**
  Update static candidate count: $ga_{iter} = 0 \wedge$ exploitation setting (Table 3.10)
else
  update $ga_{iter} = ga_{iter} + pop\ size$
end if
if static count exceed local convergence threshold: ($ga_{iter} > threshold$) **then**
  update exploration setting: $gain$, mu (3.1), $pop\ size$ (3.2), & $threshold$ (3.3)
  update remaining evaluation number, $gen\ iter$=(3.2)×($opt\ gen - Generation$)
end if
Check customised stopping criteria:
if ($mu > max\ mu$) $\vee$ ($pop\ size > max\ pop$) $\vee$ ($threshold > gen\ iter$) **then**
  Exceed operating parameter upper limit: $break$
end if
Enable full exploration-exploitation cycle:
if (mu = 0.1) $\wedge$ ($opt\ gen$ - current $Generation < Minimum\ Convergence\ Gen$) **then**
  Allow room for convergence: $optgen = optgen + MinimumConvergenceGen$
end if
end while
return $Dist\ g_{best}$, $con\ iter$, $con\ max$, ga_{iter}, $threshold$, $gen\ iter$, $opt\ gen \wedge$ stopping message

Appendix E Hydraulic System Dataset Visualisation

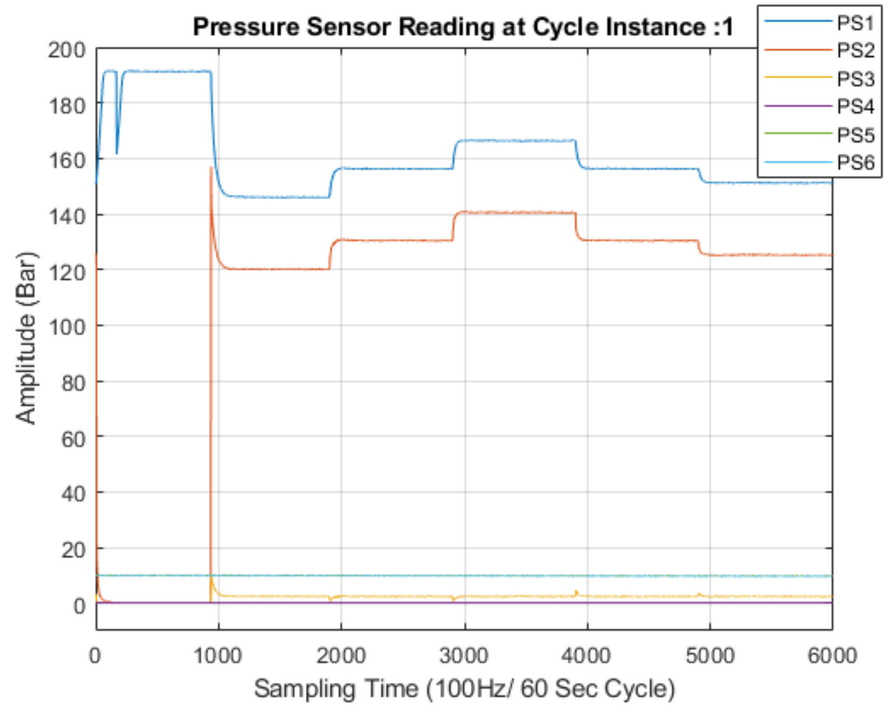


Figure E.1 Hydraulic System: Pressure PS Reading

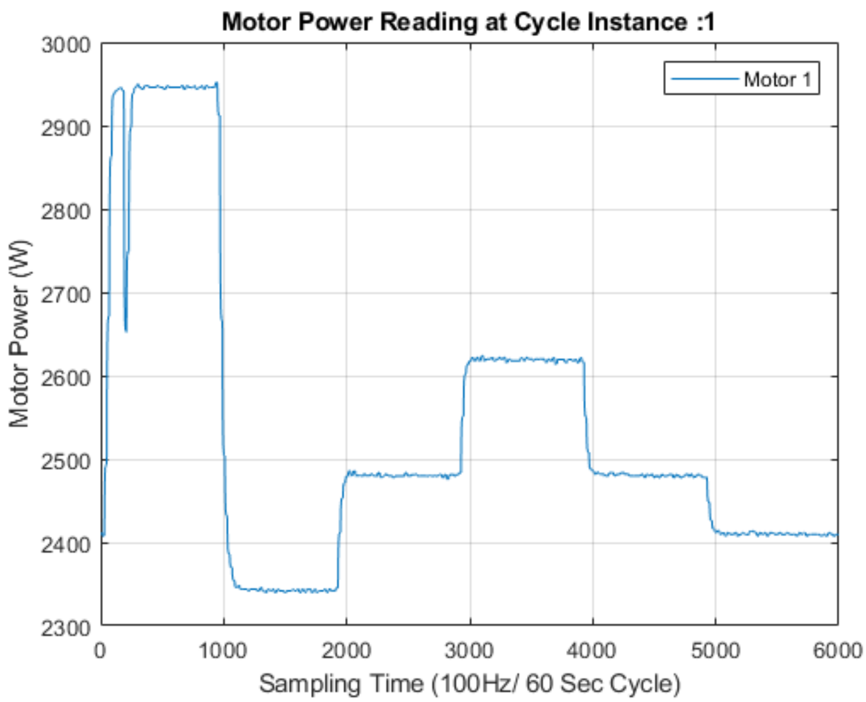


Figure E.2 Hydraulic System: Motor Power EPS1 Reading

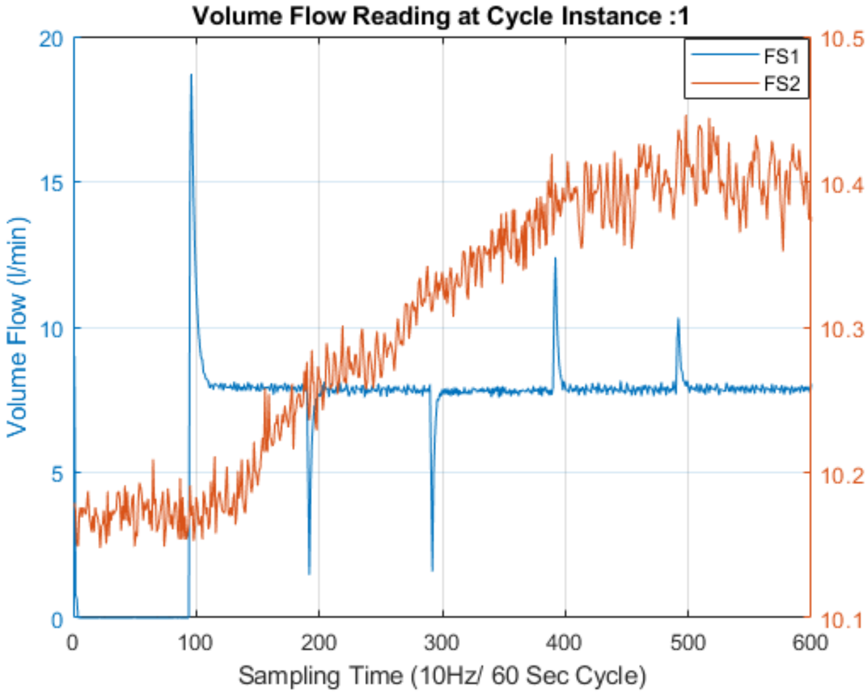


Figure E.3 Hydraulic System: Flow Rate FS Reading

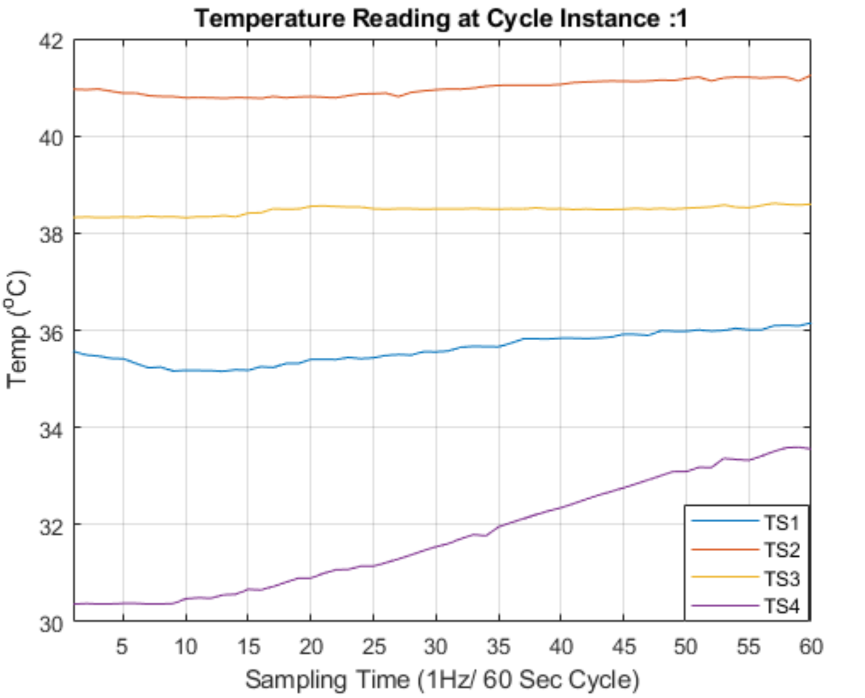


Figure E.4 Hydraulic System: Temperature TS Reading

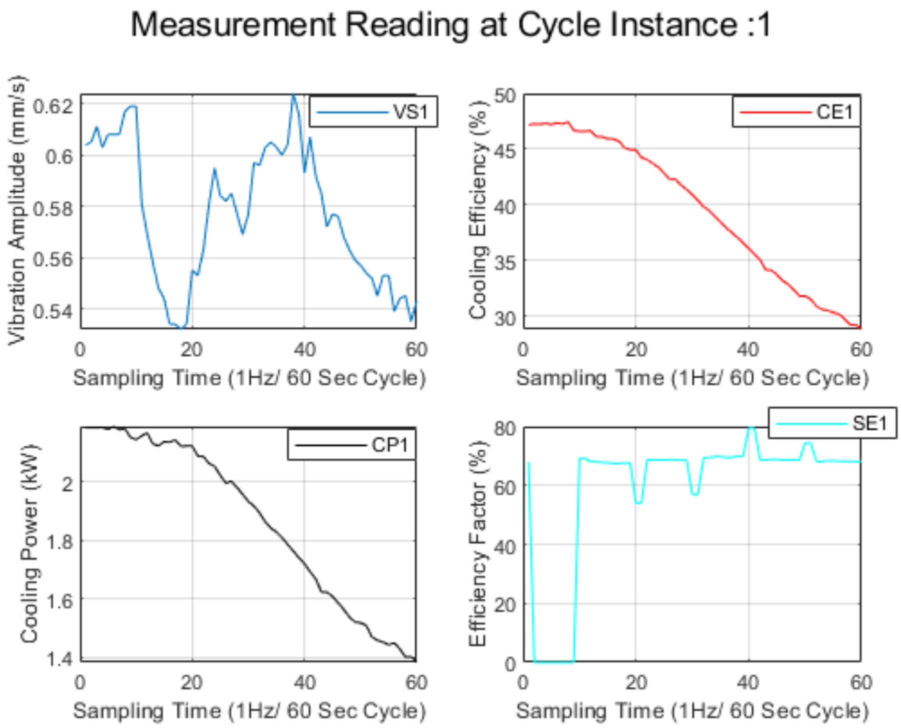


Figure E.5 Hydraulic System: Sensor Reading

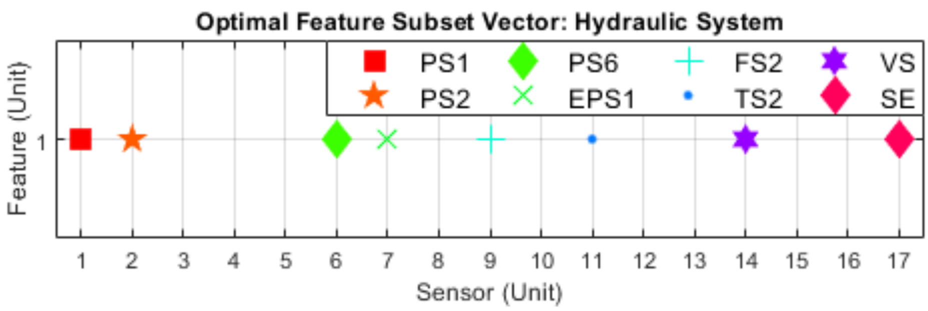


Figure E.6 Hydraulic System: Optimal Feature Subset Vector

Appendix F Pumps Mechanical Analysis Dataset Visualisation

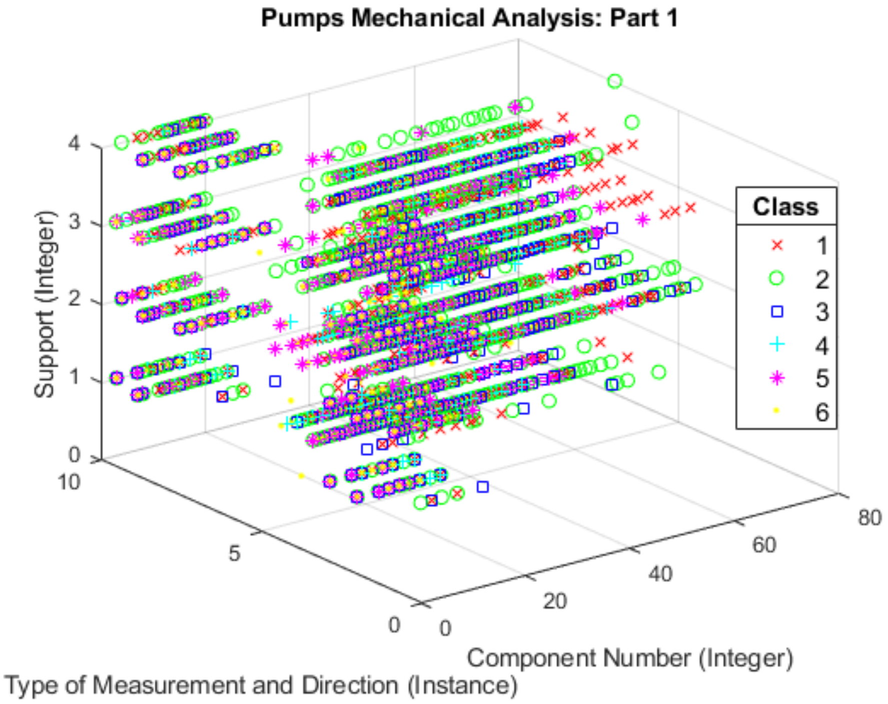


Figure F.1 3D Scatter Diagram for Pumps Component Number, Type of Measurement and Direction and Support

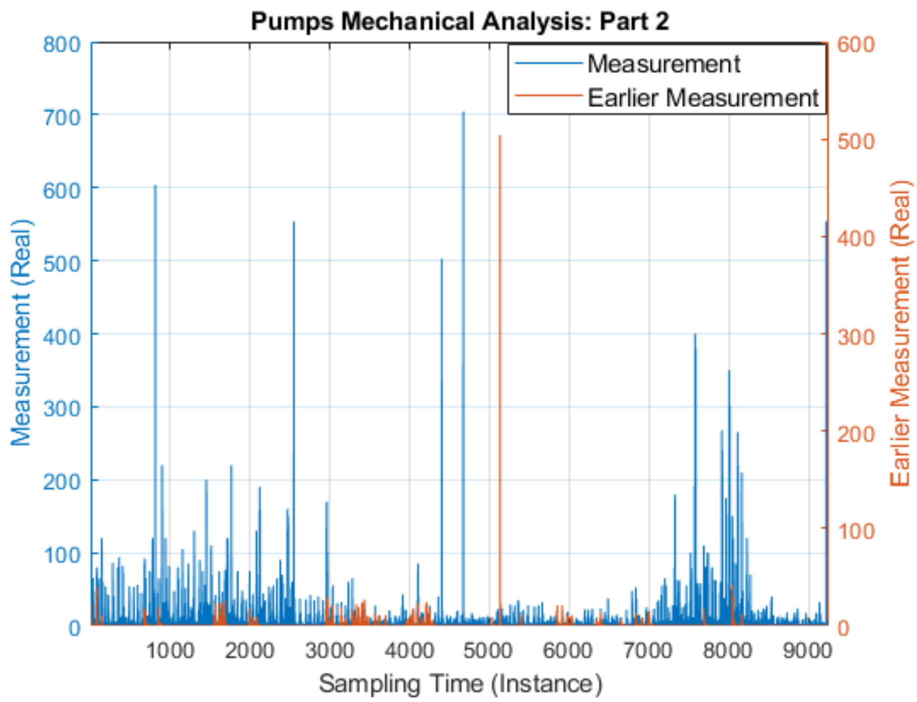


Figure F.2 Pumps Reading for Measurement: Current and Earlier

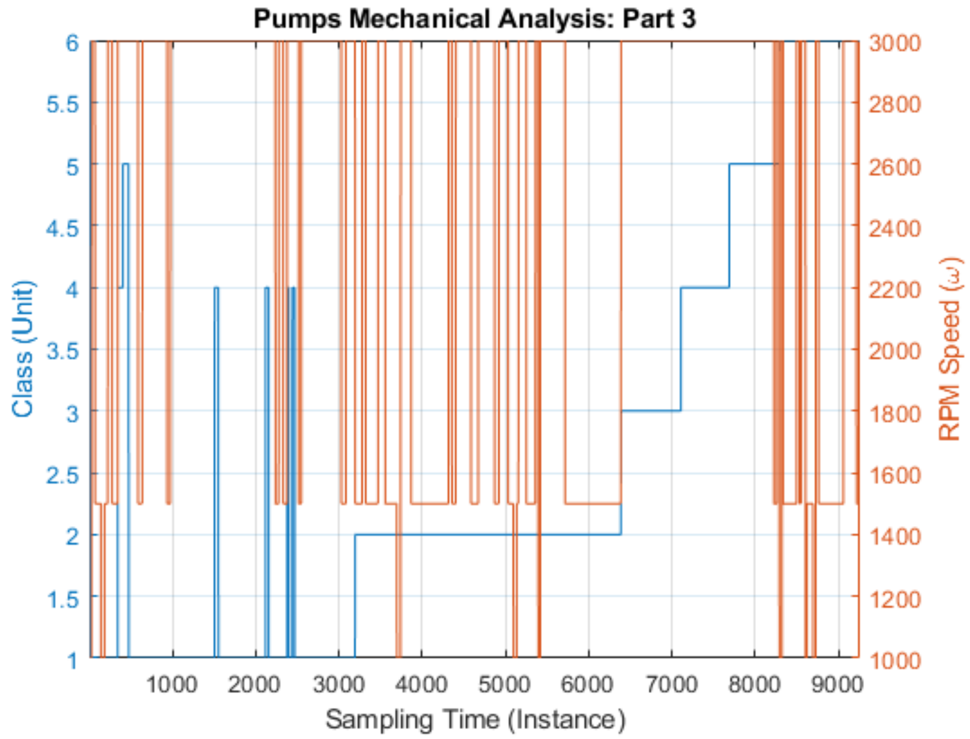


Figure F.3   Pumps Reading for Class Output and Speed

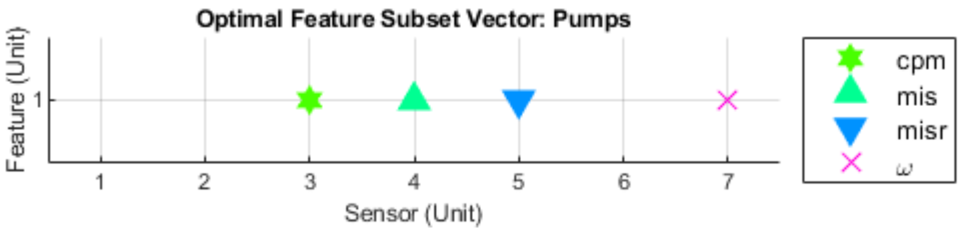


Figure F.4   Pumps: Optimal Feature Subset Vector

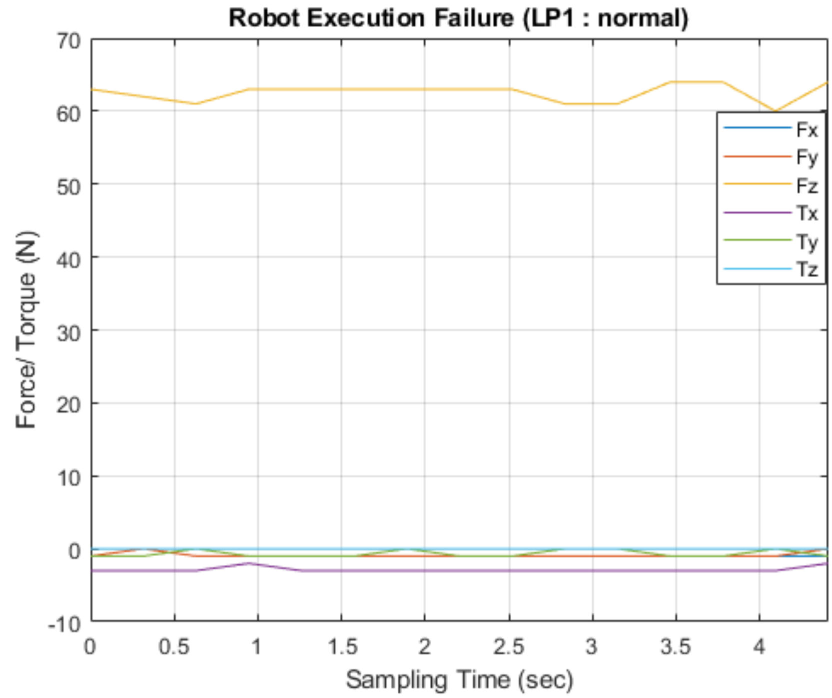


Figure G.1 Triaxial Sensor Reading for Condition: Normal

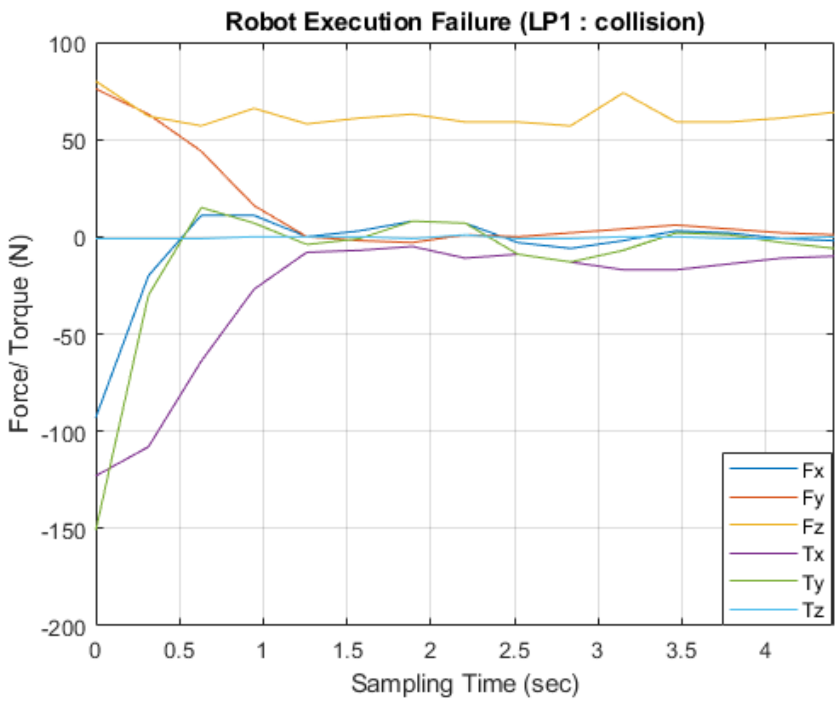


Figure G.2 Triaxial Sensor Reading for Condition: Collision

Figure G.3 2D Scatter Diagram for Robot Execution Failure Statistical Feature: average and standard deviation

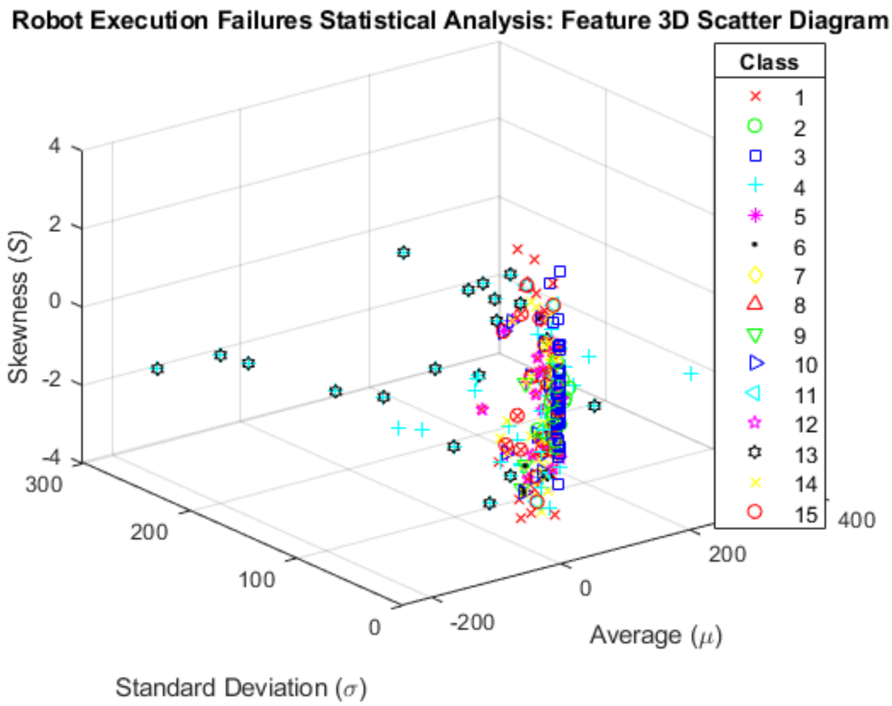


Figure G.4 3D Scatter Diagram for Robot Execution Failure Statistical Feature: average, standard deviation and skewness

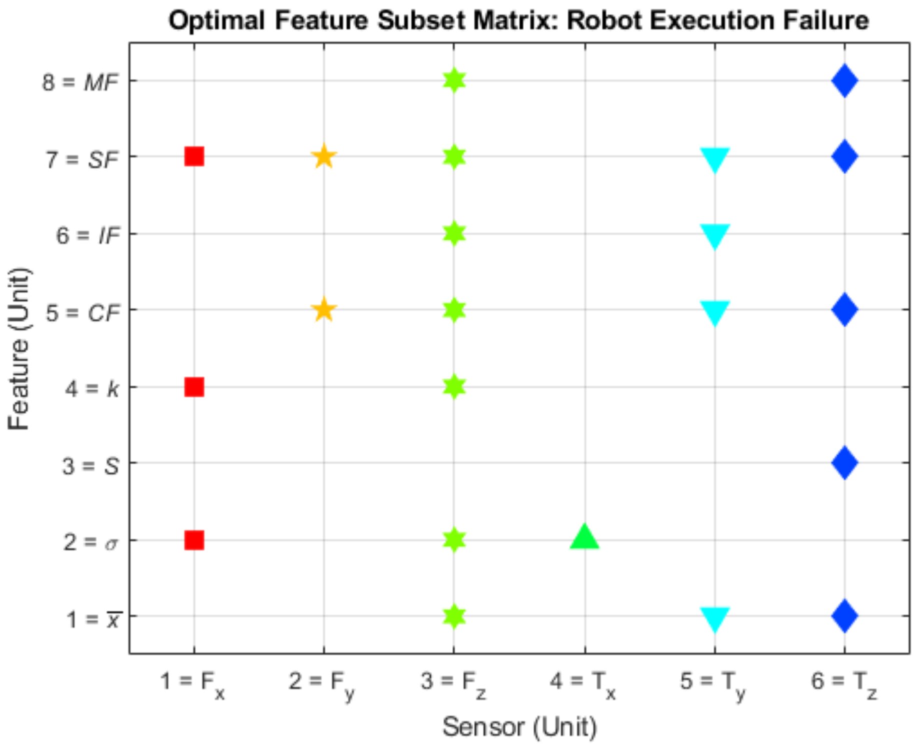


Figure G.5 Robot Execution Failures: Optimal Feature Subset Matrix

Appendix H Centrifugal Pump Residual Analysis Dataset Visualisation

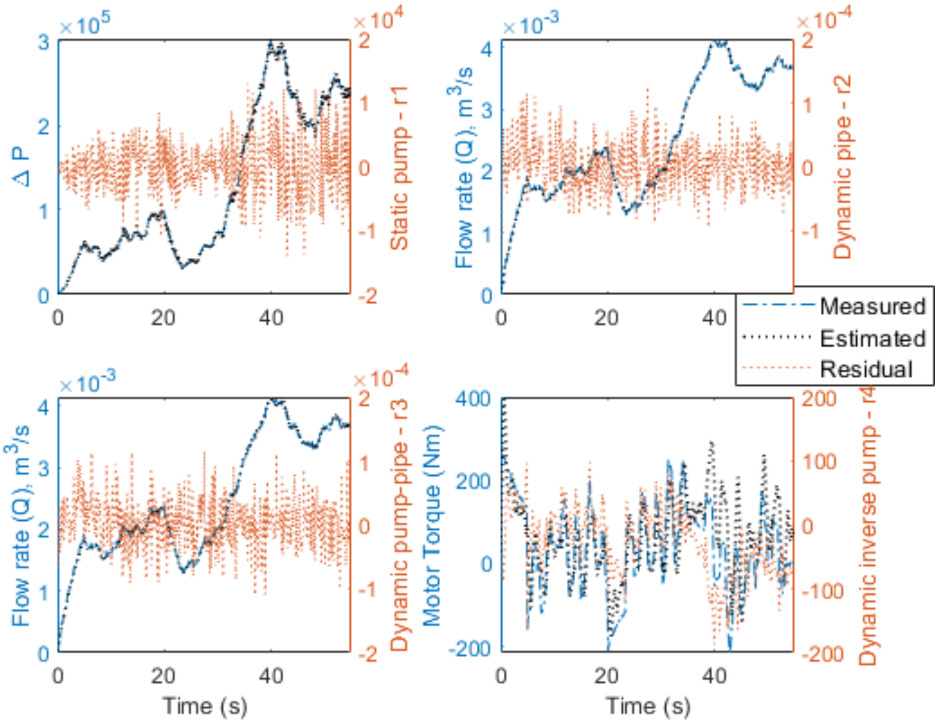


Figure H.1 Centrifugal Pump Model Validation

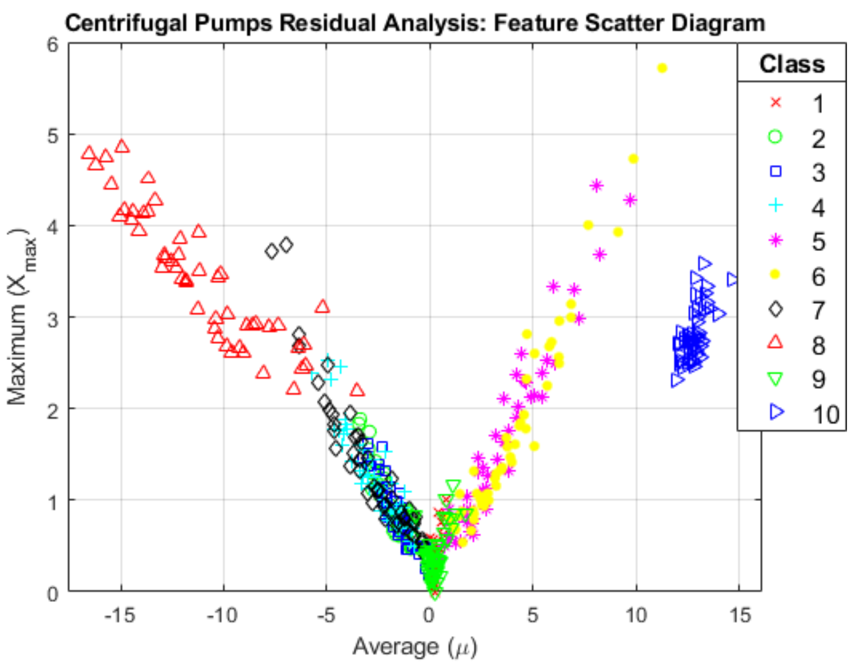


Figure H.2 2D Scatter Diagram for Residual Statistical Feature: average and maximum amplitude

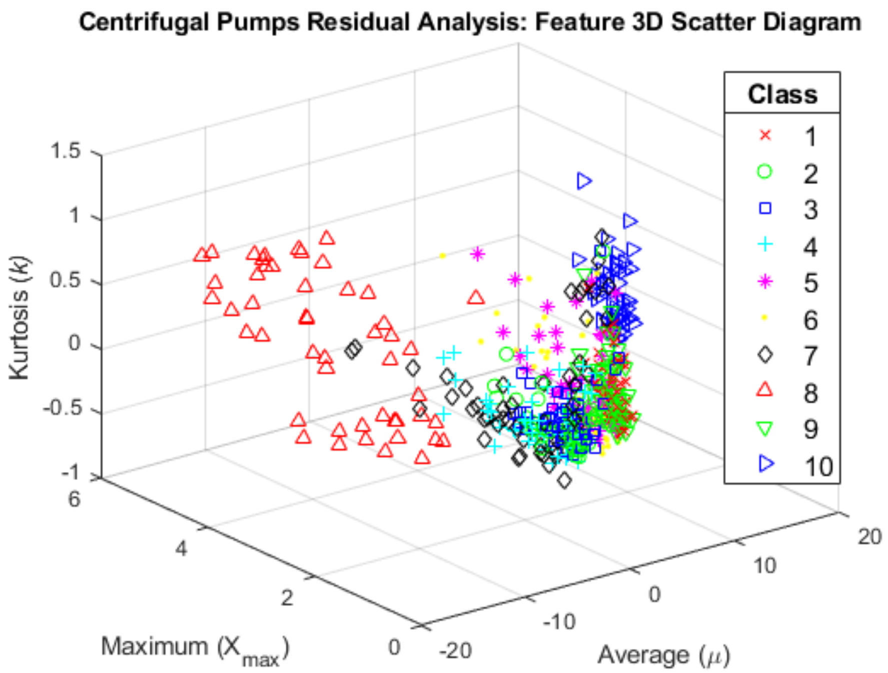


Figure H.3 3D Scatter Diagram for Residual Statistical Feature: average, maximum amplitude and kurtosis

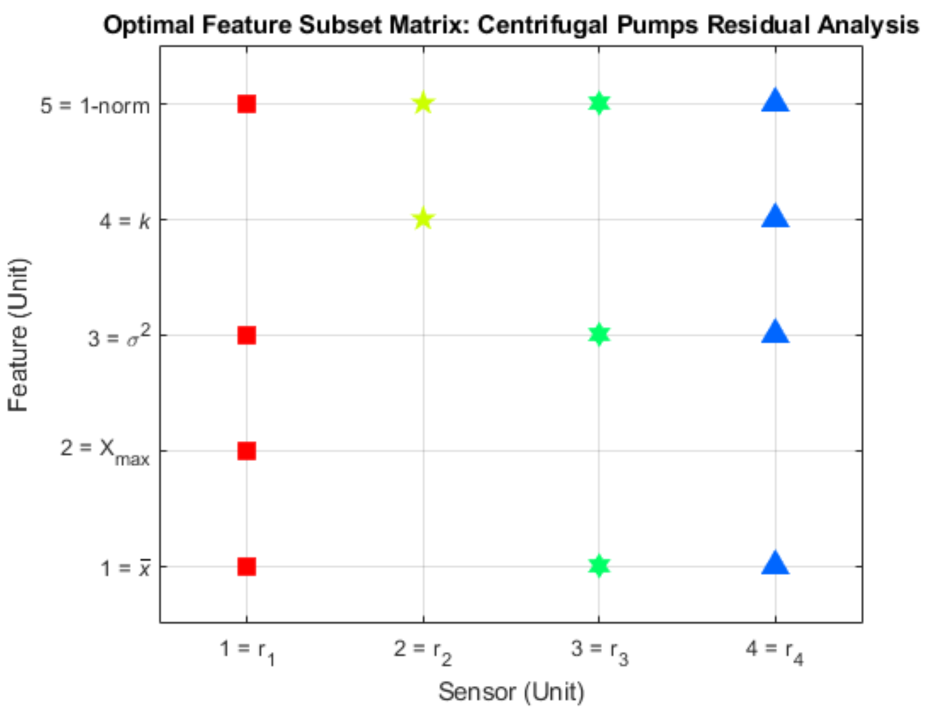


Figure H.4 Centrifugal Pump Residual Analysis: Optimal Feature Subset Matrix

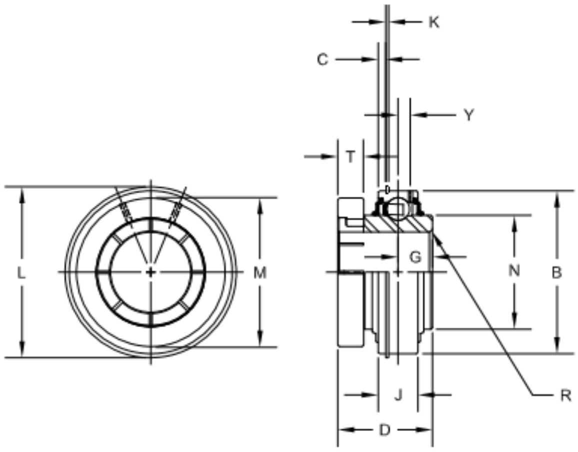
Appendix I MFS-RDS Bearing Specifications

ER-K – 200 Series Intermediate Duty Spring Locking Ball Bearing

ER-K

Interchange: *GER, ER-T*

Photo Shows an ER Adapter Series Ball Bearing Unit



Product Features

Broad range of sealing options
Spring locking setscrew mount
Sealed & relubricatable
Spherical O.D.
See Features and Benefits for additional info on pages 286 - 287.

Bearing Dimensions

Size Code	Shaft Diameter	Part Number	B O.D.	J Outer Ring Width	L Snap Ring O.D.	C	D	G	K	M	N	R	T Width	T Tap	Y	Approx. Weight
204	1/2	ER8K◆● □Δ	1.8504	0.6240	2 1/16	3/32	1 15/64	0.4050	3/64	1 1/2	1.154	0.04	23/64	#10-32	0.142	0.62
	5/8	ER10K◆● □Δ														0.55
	3/4	ER12K◆● □Δ														0.54
	20.00	*ER204K⊠⊠ ⊠Δ*	*47.0000*	*15.8500*	*52.40*	*2.40*	*30.96*	*10.2900*	*1.20*	*38.10*	*29.310*	*1.00*	*8.70*	*M6X1*	*3.610*	*0.20*
205	7/8	ER14K◆● □Δ	2.0472	0.7490	2 17/64	3/32	1 13/32	0.5080	3/64	1 5/8	1.313	0.04	23/64	1/4-28	0.185	0.65
	15/16	ER15K◆● □Δ														0.63
	1	ER16K◆● □Δ														0.61
	25.00	*ER205K⊠⊠ ⊠Δ*	*52.0000*	*19.0250*	*57.60*	*2.40*	*34.92*	*12.9000*	*1.20*	*41.40*	*33.350*	*1.00*	*8.70*	*M6X1*	*4.700*	*0.30*
206	1 1/8	ER18K◆● □Δ	2.4409	0.8740	2 21/32	3/32	1 17/32	0.6250	3/64	2	1.587	0.04	7/16	1/4-28	0.224	0.96
	1 3/16	ER19K◆● □Δ														0.94
	1 1/4	ER20SK◆● □Δ														0.90
207	1 1/4	ER20K◆● □Δ	2.8346	0.9365	3 5/64	1/8	1 47/64	0.6880	1/16	2 1/4	1.847	0.04	7/16	5/16-24	0.256	1.75
	1 3/8	ER22K◆● □Δ														1.70
	1 7/16	ER23K◆● □Δ														1.62
208	1 1/2	ER24K◆● □Δ	3.1496	1.0927	3 25/64	1/8	1 31/32	0.7500	1/16	2 9/16	2.083	0.06	7/16	5/16-24	0.297	2.18
	40.00	*ER208K⊠⊠ ⊠Δ*	*80.0000*	*27.7550*	*86.10*	*3.20*	*49.22*	*19.0500*	*1.60*	*65.00*	*52.910*	*1.60*	*11.10*	*M8X1.25*	*7.540*	*1.00*
209	1 5/8	ER26K◆● □Δ	3.3465	1.0927	3 15/32	1/8	1 31/32	0.7500	1/16	2 3/4	2.281	0.06	7/16	5/16-24	0.297	2.28
	1 11/16	ER27K◆● □Δ														2.22
	1 3/4	ER28K◆● □Δ														2.15
210	1 7/8	ER30K◆● □Δ	3.5433	1.1240	3 25/32	1/8	2 5/64	0.7500	3/32	3	2.475	0.06	5/16	5/16-24	0.265	2.75
	1 15/16	ER31K◆● □Δ														2.61
211	2	ER32K◆● □Δ	3.9370	1.1860	4 11/64	1/8	2 15/64	0.8750	3/32	3 1/4	2.749	0.08	5/16	5/16-24	0.298	3.38
	2 3/16	ER35K◆● □Δ														3.07
212	2 1/4	ER36K◆● □Δ	4.3307	1.2490	4 9/16	1/8	2 19/32	1.0000	3/32	3 1/2	3.012	0.08	5/16	3/8-24	0.330	4.48
	2 3/8	ER38K◆● □Δ														4.38
	2 7/16	ER39K◆● □Δ														4.19
214	2 1/2	ER40K◆● □Δ	4.9213	1.3740	5 5/32	5/32	2 47/64	1.0620	7/64	3 15/16	3.433	0.08	3/4	3/8-24	0.374	5.92
	2 11/16	ER43K◆● □Δ														5.49
215	2 7/8	ER46K◆● □Δ	5.1181	1.4990	5 1/2	5/32	3	1.3130	7/64	4 3/8	3.632	0.08	3/4	3/8-24	0.374	6.60
	2 15/16	ER47K◆● □Δ														6.37
216	3	ER48K◆● □Δ	5.5118	1.6865	5 7/8	5/32	3 3/8	1.3130	7/64	5	3.920	0.12	3/4	3/8-24	0.406	8.05
	3 3/16	ER51K◆● □Δ														7.56

Additional Notes

Please call 1-866-REXNORD for availability

Bearing O.D. tolerance for size code 204, +.0000 in/-.0005 in *(+0.000 mm/-0.013 mm)*; for size code 205 thru 208, +.0000 in/-.0006 in *(+0.000 mm/-0.015 mm)*; for size code 209 thru 212, +.0000 in/-.0008 in *(+0.000 mm/-0.020 mm)*; for all other size codes, +.0000 in/-.0010 in *(+0.000 mm/-0.025 mm)*

Lip seals standard

◆ Available with E1 viton seals for all size codes

Available with free running style seals, add suffix ● FF, □ HFF or Δ MHFF for all size codes

For the Selection Guide, Load Ratings and Speed Limits, see the Link-Belt 200 Series Ball Bearing Engineering section on pages 290 - 298.

Note: Dimensions subject to change. Certified dimensions of ordered material furnished on request.

Replacement Insert

Unmounted Replacement Bearings - 390 *Ball Bearings*

Figure I.1 ER-K Ball Bearing Specifications

Appendix J MFS-RDS Dataset Visualisation

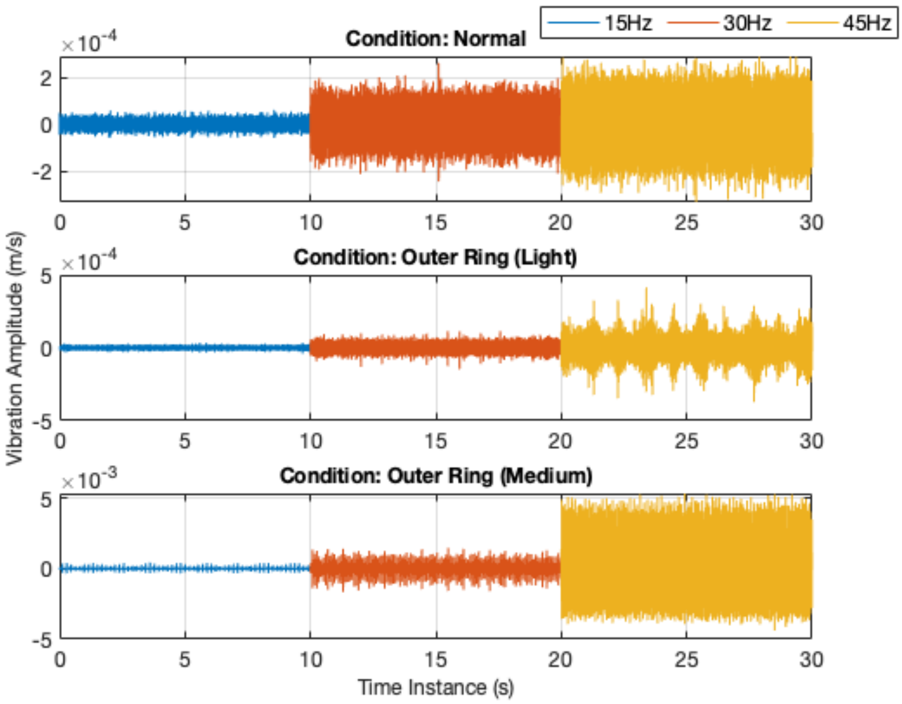


Figure J.1 MFS-RDS Vibration Sensor Reading: Part 1

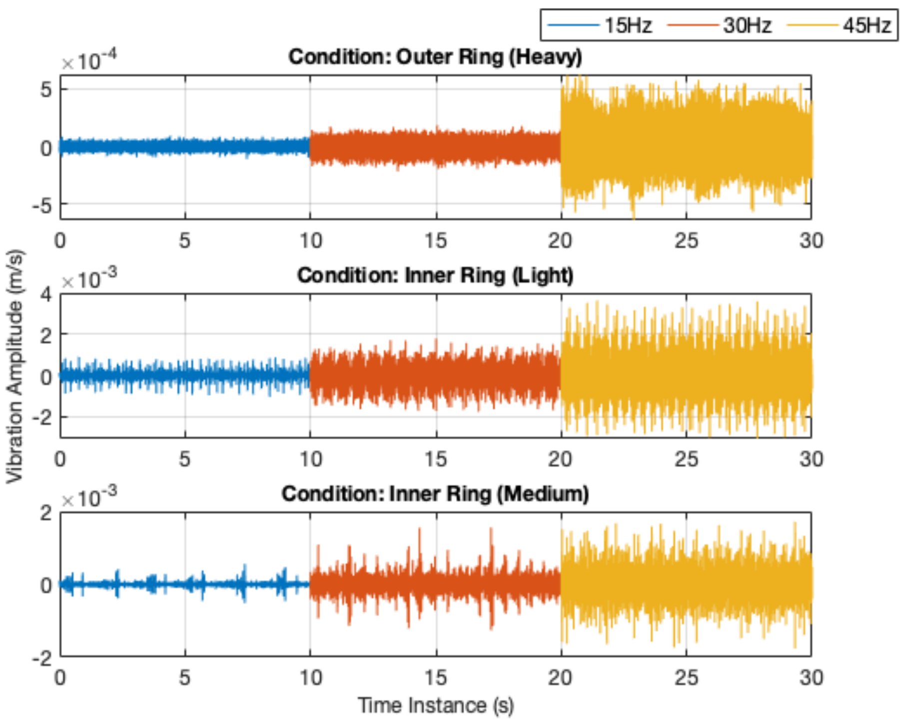


Figure J.2 MFS-RDS Vibration Sensor Reading: Part 2

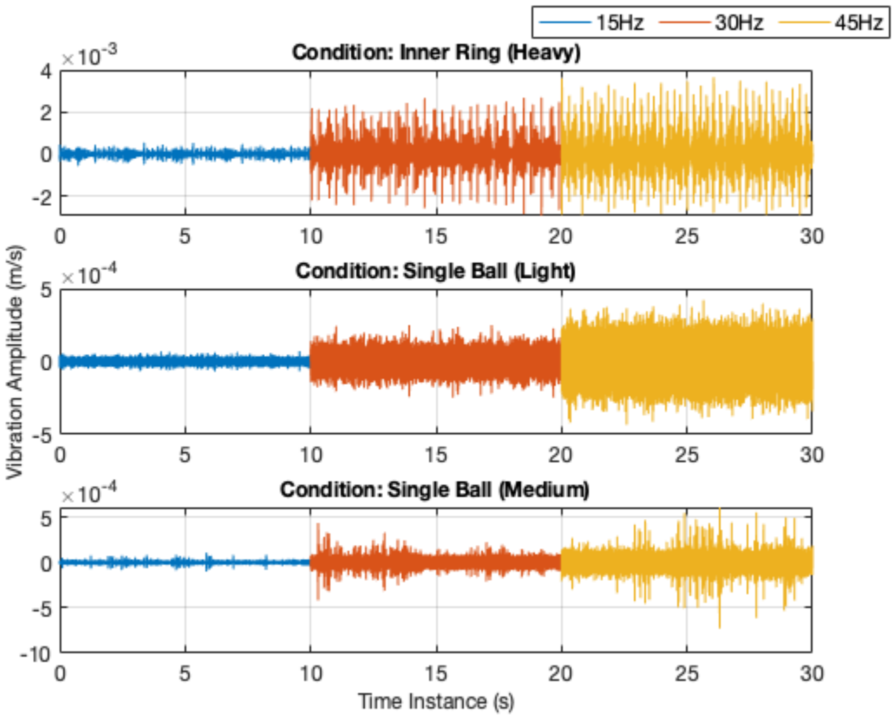


Figure J.3 MFS-RDS Vibration Sensor Reading: Part 3

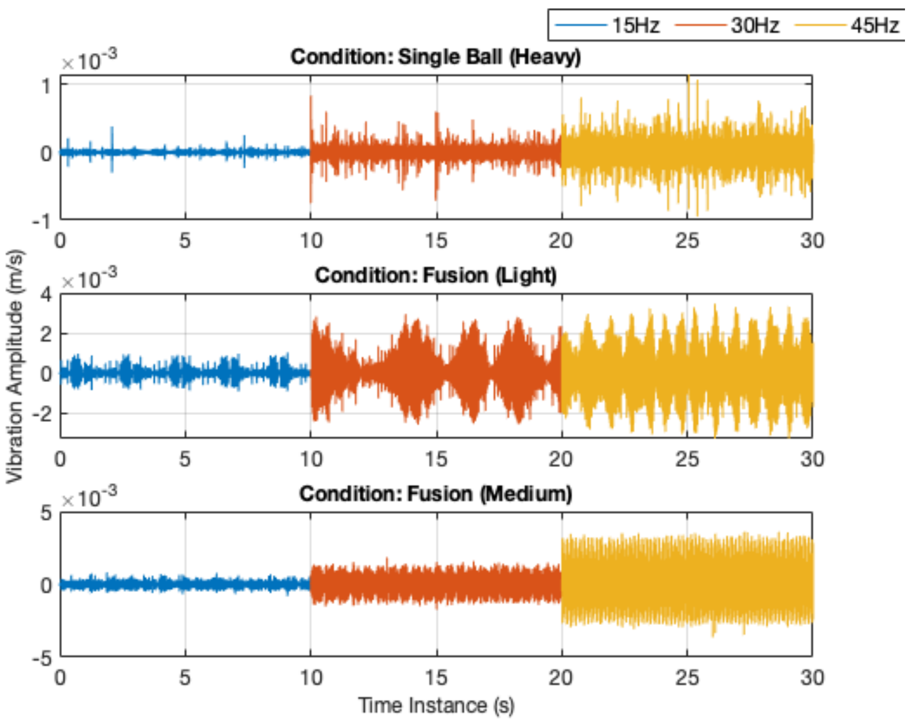


Figure J.4 MFS-RDS Vibration Sensor Reading: Part 4

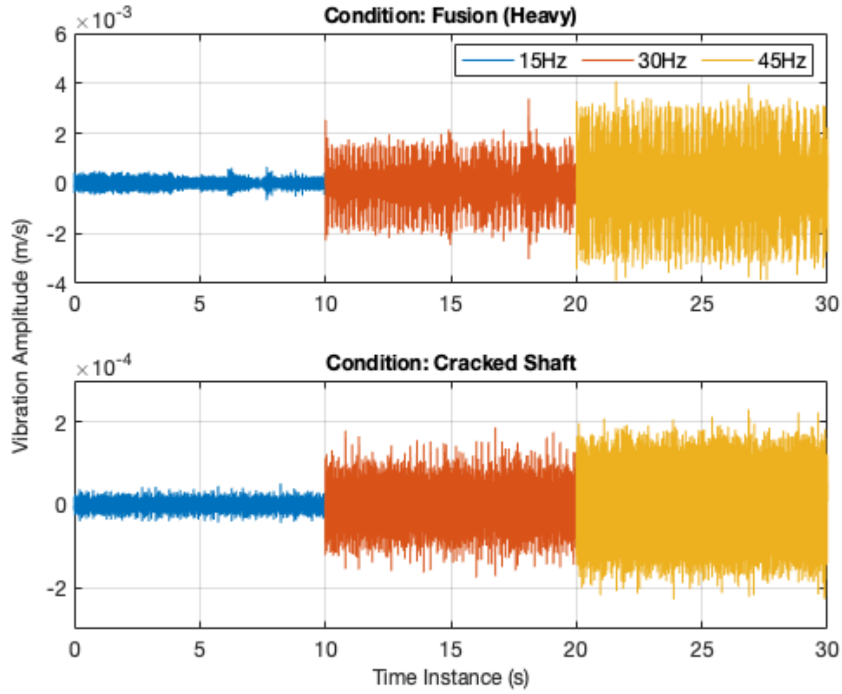


Figure J.5 MFS-RDS Vibration Sensor Reading: Part 5.

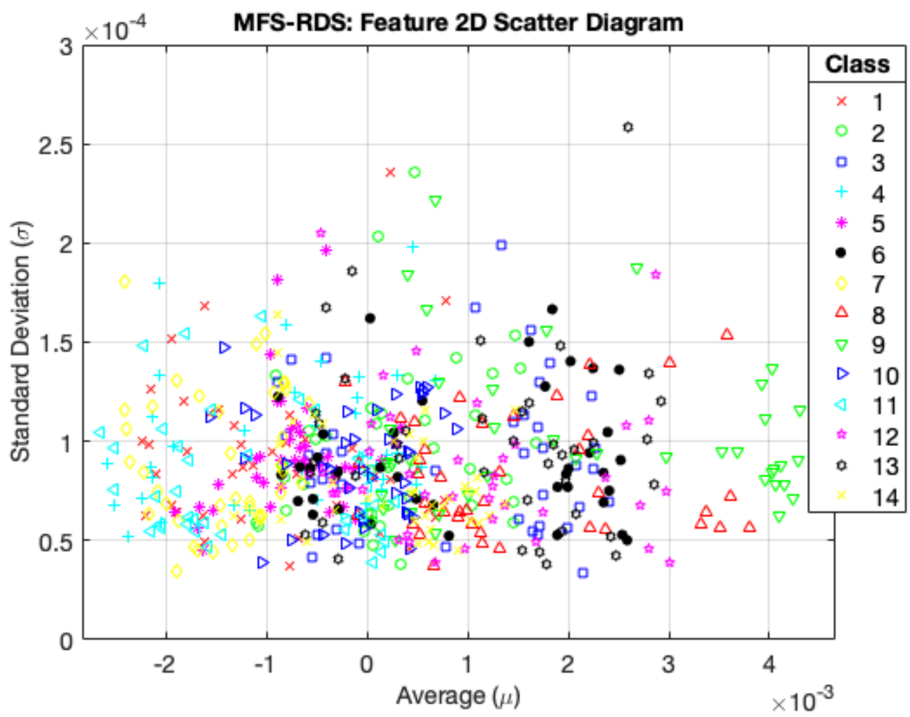


Figure J.6 2D Scatter Diagram for MFS-RDS Statistical Feature: average and maximum amplitude

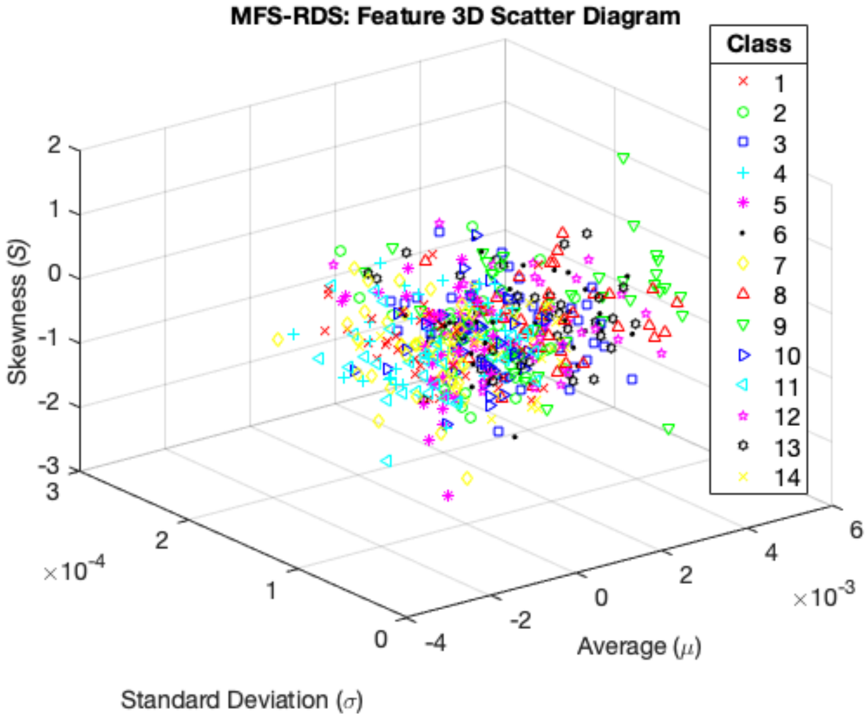


Figure J.7 3D Scatter Diagram for MFS-RDS Statistical Feature: average, maximum amplitude and skewness

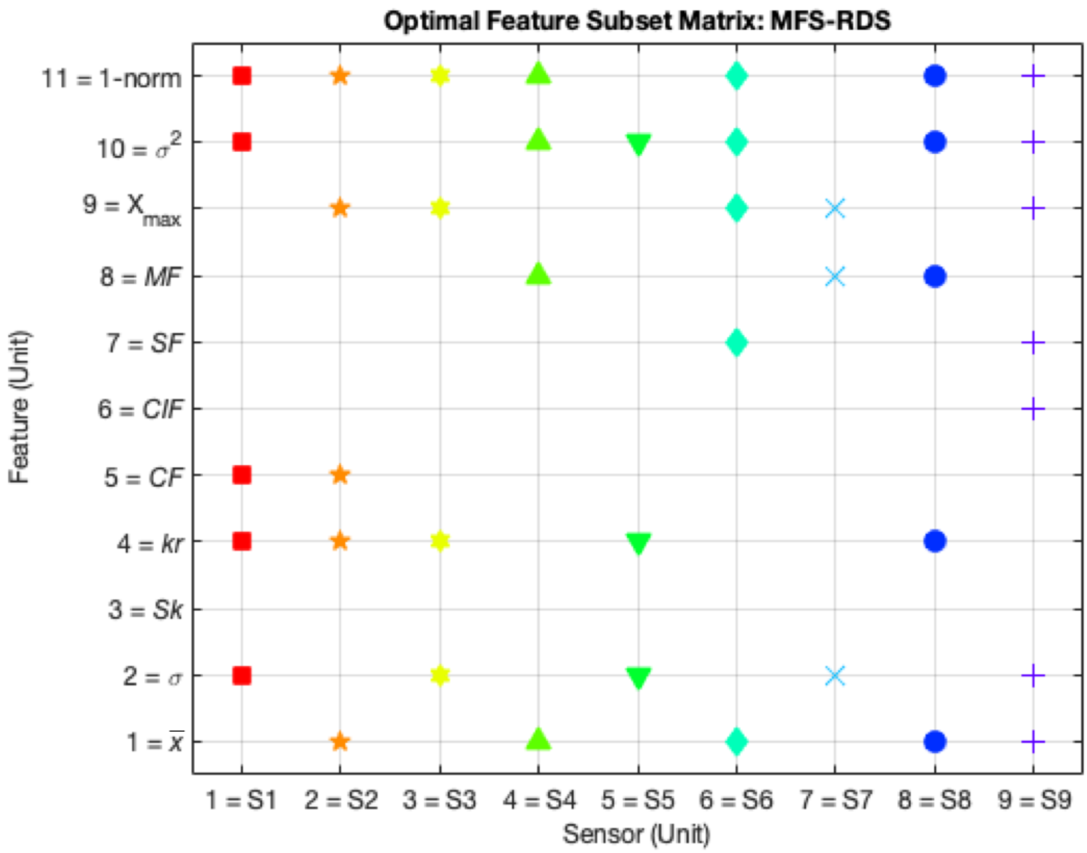


Figure J.8 MFS-RDS: Optimal Feature Subset Matrix

Appendix K Vibration Accelerometer Specifications

Wilcoxon
SENSING TECHNOLOGIES

General purpose compact accelerometer

780A

SPECIFICATIONS

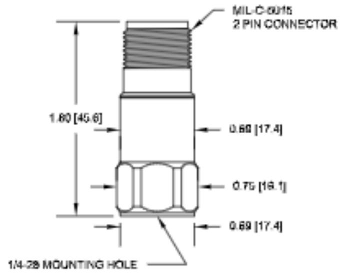
Sensitivity, ±5%, 25°C		100 mV/g
Acceleration range		80 g peak
Amplitude nonlinearity		1%
Frequency response:	**±5%**	3 - 5,000 Hz
	±10%	1 - 9,000 Hz
	±3 dB	0.5 - 14,000 Hz
Resonance frequency		30 kHz
Transverse sensitivity, max		5% of axial
Temperature response:	**–55°C**	–20%
	+120°C	+10%
Power requirement:		
Voltage source		18 - 30 VDC
Current regulating diode		2 - 10 mA
Electrical noise, equiv. g, nominal:		
Broadband	**2.5 Hz to 25 kHz**	700 µg
Spectral	**10 Hz**	10 µg/√Hz
	100 Hz	5 µg/√Hz
	1,000 Hz	5 µg/√Hz
Output impedance, max		100 Ω
Bias output voltage		12 VDC
Grounding		case isolated, internally shielded
Temperature range		–55° to +120°C
Vibration limit		500 g peak
Shock limit		5,000 g peak
Electromagnetic sensitivity, equiv. g, max		70 µg/gauss
Sealing		hermetic
Base strain sensitivity, max		0.0002 g/µstrain
Sensing element design		PZT, shear
Weight		62 grams
Case material		316L stainless steel
Mounting		1/4-28 UNF tapped hole
Output connector		2 pin, MIL-C-5015 style
Mating connector		R6 type
Recommended cabling		J10 / J9T2A

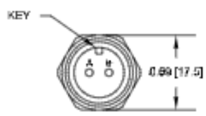
Accessories supplied: SF6 mounting stud; calibration data (level 2)

CE

Key features

- Compact, lightweight
- Certified versions available for use in hazardous areas
- API 670 compliant
- Manufactured in ISO 9001 facility





Connections	
Function	Connector pin
power/signal	A
common	B
ground	shell

Note: Due to continuous process improvement, specifications are subject to change without notice.
This document is cleared for public release.

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98957 Rev.D.2 09/18

Figure K.1 Wilcoxon 780-A Sensor Specifications

Appendix L OROS 16 channel instrument analyzer model OR36 V3 User Manual

OROS 3-Series/NVGate User's Manual

OR36/OR38

OR36 & OR38 covers high end applications with multi-channels chassis. They offer from 4 to 32 universal inputs, 2 ext synch, 2 generators and optional auxiliary channels supporting generators, trigger/tach and parametric inputs.

FRONT PANELS

	OR38	OR36
Inputs	1 to 32 Universal Inputs	1 to 16 Universal Inputs
Out.	Generators 1 & 2	Generators 1 & 2
Ext.	External Sync.1 & 2	External Sync 1 & 2
Aux.	Auxiliary connectors[1] 1 to 4	Auxiliary connectors[1] 1 to 4
Overview		

The universal inputs gather both dynamics and parametric input in the same board and connector. The type of use of the universal inputs is selectable by software (NVGate®) during the analyzer operations.

The universal inputs fulfill all the performances, precision and operability of each specific input type.

For each input connector LED shows the current status:

Color	Input type	Signal level
Green	Dynamic	FS[2]-30 dB < Signal < FS
Cyan	Dynamic	0 < Signal < FS-30 dB
Red	Dynamic/Parametric	Signal > FS (Overload)
Yellow	Parametric	FS-30 dB < Signal < FS
Purple	Parametric	0 < Signal < FS-30 dB
Off	Inactive	N.A.

[1] Depending on the purchased options

[2] Full scale

M002-115-4 - 9 -

Figure L.1 OR36 V3 User Manual: Page 1

LATERAL PANEL

With the universal inputs and the adapted connection kit, the OR36 and OR38 can hold signal conditioning modules called XPod (dockable eXPander module).

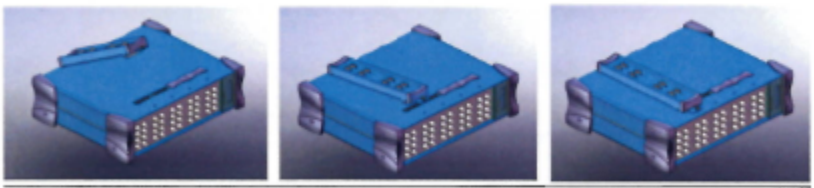
The XPod is a device that can be fixed on the OR36/OR38 side. Each XPod is associated to a block of 8 inputs.

The following optional XPod are available:

- Bridge signal conditioning for strain gauges, dynamic pressure and force measurements.
- Thermocouple and RTDs for temperature measurements.

To fix the XPod on the analyzer:

1. **Warning:** do not plug or unplug the XPod when the analyzer is powered on, shut it down for this operation.
2. lock the XPod hook in the notch on the back of right side of the analyzer,
3. Down the XPod to the corresponding connector on the side of the analyzer,
4. Secure the XPod on the analyzer with the screw on the extension key of the XPod



Note: When travelling, fix the XPod on the analyzer to avoid any damages. When there is no XPod, fix the rubber cover on the analyzer. There are two rubber covers on the XPod which allows having a cover left if one is lost.

BACK PANEL

The back panel supports the connectivity, power supply and accessories connections:

A. 2 Ethernet (1 Gb/s) connectors for connection to PC and cascade of analyzers.
    - Connect the PC to IN
    - In cascade mode connect the PC to first analyzer (master) to IN. Next units are daisy chained (OUT -> IN, OUT- > IN, etc...) in cascaded mode.
    - Cable required Category 5 unshielded twisted-pair. Use the blue cables.

B. 2 clock synchronization connectors (100 Mb/s Ethernet)
    - Do not use while using a sole analyzer
    - Daisy chain from Master unit to the next one in cascaded mode (OUT -> IN, OUT- > IN, etc...)

Figure L.2 OR36 V3 User Manual: Page 2

OROS 3-Series/NVGate User's Manual

C. DC power in XLR connector. To be plug with the external power supply. Warning do not mix the OR38 and OR36 power supply.

D. Mobi-disk . The mobi-disk holds the recorded raw data.

- Power off the analyzer prior removing or inserting it.
- When using the analyzer without the Mobi-disk plugged-in, use the obturator cover to protect the internal part of the analyzer

E. Disk activity LED. The LED will flash while data are written on or read from the disk.

F. USB 2.0 for raw data recording. To record on a external disk, power off the analyzer, remove the Mobi-Disk (put the obturator cover), plug you USB memory device and power on. The raw data will be saved on the memory device. Warning the write speed on your memory device may lead to a throuput error, check the performance before using it for actual measurements

G. Interface connector: RS-232 for remote control through RJ11 connector

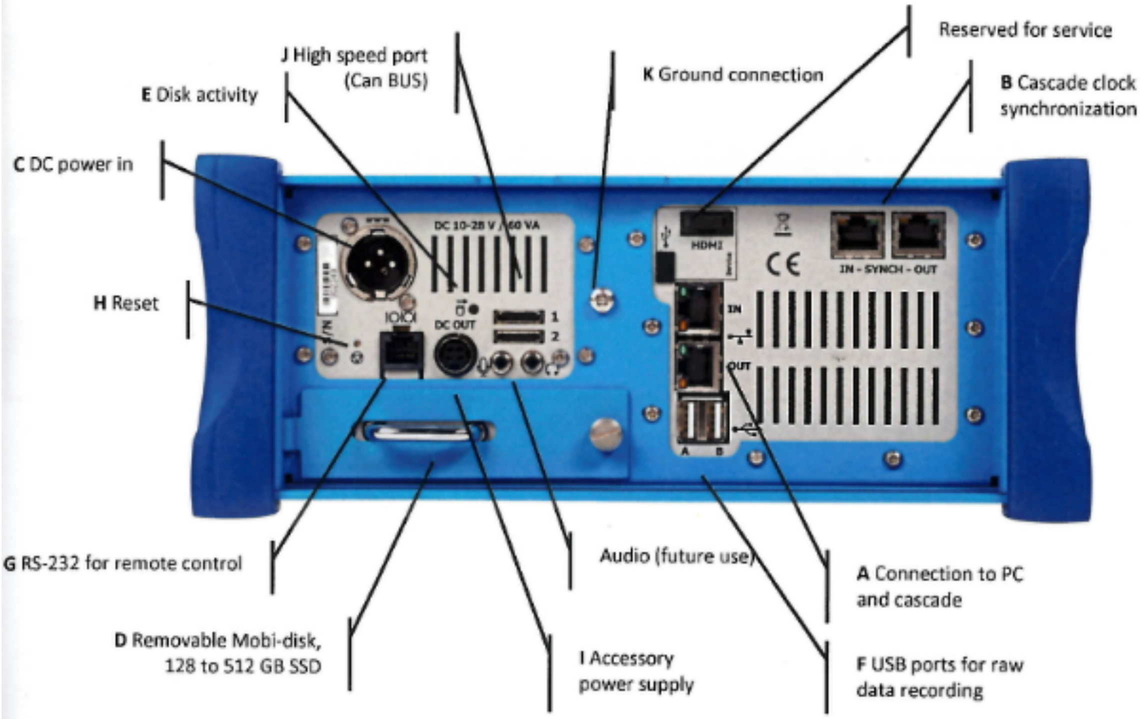
H. Reset. To be used when your analyzer does no respond to any command. Insert a paper clip in the hole and press smoothly.

I. Accessory Power supply. This connector provides power supply for external use (transducer, tachometer, etc power supply). The available voltage and power are:

- +5 V, 3 W, 1.6 A
- +9 V, 6 W, 650 mA
- +24 V, 6 W, 25 mA

J. High speed port: Used for connection the CAN bus probe

K. Ground connection. Use this screw to connect the analyzer to the ground potential

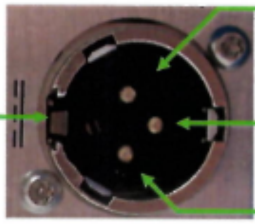


M002-115-4 - 11 -

Figure L.3 OR36 V3 User Manual: Page 3

POWER SUPPLY

DC power supply connector



The analyzer may be powered from an external DC voltage to replace the external power supply. The power voltage and current must fulfill the following conditions:

OR36 Power supply

Power	< 60 VA	
External AC Power supply	Voltage	100 to 240 VAC / 1.7 A max
	Frequency	50/60 Hz
DC	Range	12 V[3] to 28 V
	Overload protection	**31 V** (over this voltage DC poles are short-circuited)
Battery	Type	**NiMh** 11 modules (no memory effect)
	Autonomy	**2 h** (4 ch 1 DSP 12.8 kS/s)
	Charge time	**2 h 30 min** (typical)
	Charge conditions	DC power supply > 18 V

OR38 power supply

Power	< 100 VA	
External AC Power supply	Voltage	100 to 240 VAC / 2.0 A max
	Frequency	50/60 Hz
DC	Range	15 V[4] to 28 V
	Overload protection	**31 V** (over this voltage DC poles are short-circuited)
Battery	Type	**NiMh** 17 modules (no memory effect)
	Autonomy	**2 h** (8 ch 1 DSP 12.8 kS/s)
	Charge time	**3 h** (typical)
	Charge conditions	DC power supply > 24 V

BATTERIES

OROS-3 Series Hardware contains an internal battery block particularly useful for autonomous operations (except for OR34) or in case of temporary power failure (all OROS-3 Series analyzers).

The batteries of OROS-3 Series Hardware are designed to provide maximum trouble-free life. To obtain the longest battery life, please follow the following advice:

[3] DC power voltage > 17 V will discard the battery
[4] DC power voltage > 22 V will discard the battery

Figure L.4 OR36 V3 User Manual: Page 4

- Temperature above normal room temperature will shorten battery life. If OROS-3 Series Hardware is stored or shipped at more than 40°C (104°F), recharge it before running the system.
- Charge the battery in cool area. The battery is in charge when OROS-3 Series Hardware is plugged to a power supply. Charge stops when the Front Panel indicates 100%.
- Never store OROS-3 Series Hardware with a discharged battery.

All batteries gradually lose their charge (the higher the temperature is, the quicker the batteries lose their charge). If you store your system for a long time without using it, recharge the batteries every two or three months. This practice will extend battery life.

FAN

The cooling fan is used to reduce the temperature inside OROS-3 Series Hardware. From the Front Panel the user can manually switch it on or switch off (for very sensitive acoustic measurements).

The fan operation will be automatically forced when the temperature inside the OROS-3 Series Hardware reaches 50°C and stops at 43°C.

WARNING. Do not cover the OR3X Hardware in order to let the ventilation operate properly

Temperature and FAN management

<table>
<tr><th>Internal temp.</th><th>Status</th><th>Fan</th></tr>
<tr><td>70°C (158°F)</td><td>Absolute max. ratings
Automatic shutdown</td><td>N.A.</td></tr>
<tr><td>60°C (140°F)</td><td rowspan="4">Normal</td><td>Auto max</td></tr>
<tr><td>50°C (122°F)</td><td>Fast</td></tr>
<tr><td>45°C (113°F)</td><td>Slow</td></tr>
<tr><td>30°C (86°F)</td><td rowspan="3">Off</td></tr>
<tr><td>0°C (32°F)</td><td>Requires a warmup which last 1 min per 1 Celsius degree below zero</td></tr>
<tr><td>-20°C (-4°F)</td><td>Do not operate</td></tr>
<tr><td>-35°C (-31°F)</td><td>Absolute min. ratings</td><td>N.A.</td></tr>
</table>

Figure L.5 OR36 V3 User Manual: Page 5

LIST OF PUBLICATIONS

Journal with Impact Factor

1. Ooi, C. S., Lim, M. H. and Leong M. S. Self-Tune Linear Adaptive-Genetic Algorithm for Feature Selection. *IEEE Access*, 2019. 7: 138211-138232. doi: 10.1109/ACCESS.2019.2942962. **(Q1, IF: 4.076)**
2. Hui, K. H. *et al.* An improved wrapper-based feature selection method for machinery fault diagnosis. *PLoS ONE*, 2017. 12(12): e0189143. doi: 10.1371/journal.pone.0189143. **(Q2, IF: 3.227)**
3. Hui, K. H., Ooi, C. S., Lim, M. H. and Leong, M. S. A hybrid artificial neural network with Dempster-Shafer theory for automated bearing fault diagnosis. *J. vibroeng.*, 2016. 18(7): 4409-4418. doi: 10.21595/jve.2016.17024 **(Q4, IF: 0.392)**

Indexed Journal

1. Ooi, C. S. *et al.* System Identification of Helical Strakes Suppressed Vortex-induced Vibration for Flexible Pipes. *Pertanika J Sci Technol.*, 2020. 28(2): 493-508. **(Indexed by Web of Science)**
2. Jeyabalan, H. *et al.* An improved turbomachinery condition monitoring method using multivariate statistical analysis. *Int. J. Mech. Eng. Tech.*, 2017. 8(5): 1147 - 1159. **(Indexed by SCOPUS)**

Indexed Conference Proceedings

1. Ooi, C. S. *et al.* Review of Underground Storage Tank Condition Monitoring Techniques. *MATEC Web Conf.*, 2019. 255: 02009. doi:10.1051/matecconf/201925502009. **(Indexed by Web of Science)**
2. Yusoff, M. D., Ooi, C. S., Lim, M. H. and Leong, M. S. A hybrid k-means-GMM machine learning technique for turbomachinery condition monitoring. *MATEC*

Web Conf., 2019. 255: 06008. doi:10.1051/matecconf/201925506008. **(Indexed by Web of Science)**

3. Hui, K. H., Ooi, C. S., Lim, M. H., and Leong, M. S. Feature selection tree for automated machinery fault diagnosis. *MATEC Web Conf.*, 2019. 255: 02004. doi: 10.1051/matecconf/201925502004. **(Indexed by Web of Science)**