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Theory and Application of Artificial Immune Systems in Fault Detection and Diagnosis in Dynamic Systems

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Dedico este trabalho à memória de meu tio e professor do Departamento de Engenharia Elétrica, Selênio Rocha Silva, que infelizmente faleceu após a finalização deste trabalho. Nunca esquecerei o apoio, a compreensão e as dicas muito úteis oferecidas durante toda a minha formação profissional na UFMG.

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Resumo

O trabalho busca contribuir no sentido de avaliar a modelagem e contextualização dos sistemas imunoinspirados, assim como a aplicação destes no problema de detecção de falhas em sistemas dinâmicos. São apresentadas muitas abordagens para este propósito, algumas delas novas, como por exemplo o método de Reconhecimento Antigênico Nebuloso, um algoritmo supervisionado de detecção inspirado no processo de maturação das células T. Outro aspecto apontado neste trabalho envolve a definição formal do problema segundo o Modelo do Perigo, com abordagens baseadas na avaliação de evidências de operação normal ou de falhas e a aplicação de abordagens tradicionais como o Algoritmo das Células Dendríticas e o Algoritmo dos Receptores Toll-Like. Os resultados obtidos com as técnicas, no problema de detecção de falhas em motor de corrente contínua e no Benchmark DAMADICS, apresentados no trabalho, são promissores e condizentes com os propósitos da tese, validando as técnicas.

Palavras-chave: Sistemas Imunoinspirados, Detecção de Falhas, Sistemas Dinâmicos, Modelagem de Algoritmos, .

Abstract

The work aims to contribute in order to assess the modeling and contextualization of artificial immune systems, as well as their application to the fault detection in dynamic systems problem. Many approaches are presented for this purpose, some of them are new, such as the Fuzzy Antigen Recognition method, a supervised detection algorithm inspired on a view on the T cells maturation process. Another aspect discussed in this work involves the formal definition of the problem according to the Danger Model, with approaches based on the evidence evaluation of normal operation or faults and the application of traditional approaches such as Dendritic Cell Algorithm and the Toll-Like Receptors Algorithm. The results obtained with the techniques, the problem of detecting faults in DC motor and DAMADICS Benchmark, presented in the study, are promising and consistent with the purposes of the thesis, validating these techniques.

Keywords: Artificial Immune Systems, Fault Detection, Dynamic Systems, Algorithm Modeling.

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List of Abbreviations

ABS	-	*Agent-Based Simulation*
AEM	-	*Anomalous Event Management* (Gerenciamento de Eventos Anômalos)
AIN	-	*Artificial Immune/Idiotypic Network* (Rede Imune/Idiotípica Artificial)
AIS	-	*Artificial Immune Systems* (Sistemas Imunes Artificiais)
AIFD	-	*Antigen Index of Fault Differentiation* (Índice Antigênico de Diferenciação da Falha)
ALa	-	*Large intensity abrupt fault* (Falha abrupta de intensidade alta)
AMe	-	*Medium intensity abrupt fault* (Falha abrupta de intensidade média)
ANN	-	*Artificial Neural Network* (Rede Neural Artificial)
APC or APCs	-	*Antigen-Presenting Cells* (Células Apresentadoras de Antígeno)
ASm	-	*Small intensity abrupt fault* (Falha abrupta de intensidade pequena)
NC	-	*Natural Computing* (Computação Natural)
NIS	-	*Nature Inspired Systems* (Sistemas Inspirados na Natureza)
AR	-	*Ambiguity Ratio* (Taxa de Ambiguidade)
CLONALG	-	*Clonal Algorithm*
CSA	-	*Clonal Selection-based Algorithms* (Algoritmos baseados na Seleção Clonal)
CSM	-	*Costimulatory molecule* (Molécula Coestimulatória)
CSPRA	-	*Conserved Self Pattern Recognition Algorithm* (Algoritmo de Reconhecimento de Padrão do Próprio Conservado)
CCAFA	-	*Cell Context-Aware Fault Alarm* (Alarme de Falha Ciente do Contexto Celular)
DCA	-	*Dendritic Cell Algorithm* (Algoritmo das Células Dendríticas)
DC Motor	-	*Direct Current Motor* (Motor de Corrente Contínua)
DDR	-	*Distinguishable Distance Ratio* (Taxa de Distinguibilidade de Distância)
DM	-	*Danger Model* (Modelo do Perigo)
DMIA	-	*Danger Model Immune Algorithm* (Algoritmo Imunoinspirado baseado no Modelo do Perigo)
DS	-	*Danger/Damage Signals* (Sinais Indicadores de Perigo/Dano)
EC	-	*Evolutionary Computation* (Computação Evolucionária)
FDD	-	*Fault Detection and Diagnosis* (Detecção e Diagnóstico de Falhas)
FDI	-	*Fault Detection and Isolation* (Detecção e Isolamento de Falhas)
FD-DM	-	*Fault Detection based on Danger Model Method*
FuzzyNSA	-	*Fuzzy Negative Selection-based Algorithm (Fuzzy model of Antigen Recognition)*
CI	-	*Computational Intelligence* (Inteligência Computacional)
IC	-	*Immunocomputation* (Imunocomputação)

IDS	-	*Intrusion Detection Systems* (Sistemas de Detecção de Intrusão)
INS	-	*Infectious-Nonself Model* (Modelo do Nonself Infeccioso)
Inc	-	*Incipient fault* (Falha incipiente)
NK	-	*Natural Killer Cells* (Células Exterminadoras Naturais)
NSA	-	*Negative Selection-Based Algorithms* (Algoritmos baseados em Seleção Negativa)
MCAV	-	*Mature Context Antigen Value*
MHC	-	*Major Histocompatibility Complex*
MLP	-	*Multi-Layer Perceptron*
MSE	-	*Mean Square Error*
NIDS	-	*Network Intrusion Detection System* (Sistemas de Detecção de Intrusão baseados em Rede)
oc-SVM	-	*One-Class Support Vector Machine* (
PAMP or PAMPs	-	*Pathogen-Associated Molecular Patterns* (Padrões Moleculares Associados a Patógenos)
PCA	-	*Principal Component Analysis* (Análise dos Componentes Principais)
PRR or PRRs	-	*Pattern Recognition Receptors*
RBF	-	*Radial Basis Function*
SDS	-	*System Dynamics Simulation*
SIS	-	*Swarm Intelligence-based Systems* (Sistemas baseados em Inteligência de Enxame)
SOM	-	*Self-Organizing Maps*
STLR	-	*Structured Toll-Like Receptor Algorithm* (Algoritmo Estruturado dos Receptores Toll-Like)
SVM	-	*Support Vector Machine* (Máquina de Vetores de Suporte)
SS	-	*Safe Signals* (Sinais indicadores de Segurança)
TCR or TCRs	-	*T-Cell Receptors* (Receptores das Células T)
TLR or TLRs	-	*Toll-Like Receptors* (Receptores Toll-Like)
TLR Algorithm	-	*Toll-Like Receptor Algorithm* (Algoritmo dos Receptores Toll-Like)

List of Symbols

α	-	*Learning rate of the participatory clustering method*
λ	-	*Significance level of the participatory clustering method*
μ	-	*Threshold for One-class SVM*
ζ_x	-	*Binding function of x in NSA*
Ag	-	*Antigen variable (most algorithms)*
Ag_k	-	*Antigen variable at an instant k (most algorithms)*
$AIFD(a)$	-	*Antigen Index of Fault Differentiation of an antigen a (DCA)*
$AR_{(i,j)}$	-	*Ambiguity Ratio of a group i related to the group j*
AT	-	*SVM tolerance index of negative class label*
$Dist(a,b)$	-	*Euclidean distance between a and b*
c_g	-	*Centroid of a group g*
$CCAFA$	-	*Cell Context-Aware Fault Alarm (DCA)*
CSM	-	*Costimulatory/Migration variable (DCA)*
CV	-	*Process control external signal (DAMADICS)*
$dr\%$	-	*Detection rate of an algorithm*
$DDR_{(i,j)}$	-	*Distinguishable Distance Ratio of a group i related to the group j*
DS	-	*Necrotic or Danger/Damage signal (DCA)*
$DS_{(k)}$	-	*Danger/Damage signal of an instant k*
$DS'_{(k)}$	-	*Normalized Danger/Damage signal of an instant k*
$DC(a)$	-	*Number of cells that collected the antigen a (DCA)*
F	-	*Liquid flow rate (DAMADICS)*
$f(\phi)$	-	*Function of a set of variables ϕ*
$fa\%$	-	*False alarm rate of an algorithm*
G_K^+	-	*Sum of positive values of K (DCA)*
G_K^-	-	*Sum of negative values of K (DCA)*
h	-	*Value for hill functions*
$J(a,A)$	-	*Jaccard coefficient of an element a related to a set A*
K	-	*Signal combination variable (DCA)*
K^+	-	*Positive values of a signal combination variable (DCA)*
K^-	-	*Negative values of a signal combination variable (DCA)*
$K(a)$	-	*Signal combination variable associated to antigen a (DCA)*
$K\alpha(a)$	-	*$K\alpha$ index of an antigen a (DCA)*
$M(a)$	-	*Number of mature cells that collected an antigen a (DCA)*

$MCAV(a)$	-	*Mature Context Antigen Value of an antigen a (DCA)*
Mtx	-	*The scattering matrix of the participatory clustering method*
Mtx_g	-	*The scattering matrix of a group g in the participatory clustering method*
P_1	-	*Liquid pressures on the valve inlet (DAMADICS)*
P_2	-	*Liquid pressures on the valve outlet (DAMADICS)*
$r_{(k)}$	-	*Residuals of a dynamic system at instant k*
r_s	-	*Radius of training data for self detection (NSA)*
$Sm(a)$	-	*Number of semimature cells that collected an antigen a (DCA)*
SS	-	*Apoptotic or Safe signal (DCA)*
$SS_{(k)}$	-	*Safe signal of an instant k*
$SS'_{(k)}$	-	*Normalized Safe signal of an instant k*
std_g	-	*Standard deviation value of a group g*
T_1	-	*Nonself area threshold of the fuzzy antigen recognition system (Detectors approach)*
T_2	-	*Self area threshold of the fuzzy antigen recognition system (Detectors approach)*
thr	-	*Self area threshold of the fuzzy antigen recognition system (Monitoring approach), also used for most thresholds*
T and T'	-	*Liquid temperature (DAMADICS)*
T_a	-	*Alert threshold of the participatory clustering method*
T_ρ	-	*Group compatibility threshold of the participatory clustering method*
T_o	-	*Observed time of a process*
T_s	-	*Sampled time of a process*
$\bar{\Delta}t(u)$	-	*Time of delay in detection in unit u*
Tr	-	*Training data*
Tr_i	-	*The i-th training data (NSA)*
Thr_{metric}	-	*Threshold of a given metric in DCA*
Ts	-	*Test data*
V_{max}	-	*Maximum value of the normalized variable*
w	-	*Window size of the participatory clustering method*
$W_{(k)}$	-	*Sliding window at the instant k*
X and X'	-	*Servomotor rod displacement (DAMADICS)*
$X_{(k,i)}$	-	*Input X of i at the instant k*
Xi_q	-	*The q-th input X of group i*
x_k	-	*Point x to be labeled at the instant k*
$Y_{(k,i)}$	-	*Output Y of i of the dynamic system at the instant k*
$\hat{y}_{(k,i)}$	-	*Measured value of output i of the dynamic system at the instant k*

Published Papers

International Journals

1. Guilherme Costa Silva, Reinaldo Martinez Palhares, Walmir Matos Caminhas, "Immune inspired Fault Detection and Diagnosis: A fuzzy-based approach of the negative selection algorithm and participatory clustering', Expert Systems with Applications, Volume 39, Issue 16, 15 November 2012, Pages 12474-12486, ISSN 0957-4174, http://dx.doi.org/10.1016/j.eswa.2012.04.066. *Most of the Chapter 4 is based on this paper.*

International Conferences

1. Guilherme Costa Silva, Reinaldo M. Palhares, Walmir M. Caminhas: A Transitional View of Immune Inspired Techniques for Anomaly Detection. IDEAL 2012: 568-577, Natal (RN), Brazil *Some important aspects of Chapter 3 are based on this paper. This work also serves as an introduction to the Chapter 5.*

Book Chapter

1. Guilherme Costa Silva, Dipankar Dasgupta. A survey of recent works in artificial immune systems. Handbook on Computational Intelligence, Volume 2 (part - III), edited by Plamen Angelov. World Scientific. 2014. *Despite being part of another project, some parts of the Chapter 3 are based on the survey.*

National Conferences (In Portuguese)

1. Guilherme Costa Silva, Carlos A. L. de Almeida, Reinaldo M. Palhares, Walmir M. Caminhas: Um sistema imunoinspirado para detecção de anomalias baseado no reconhecimento antigênico e na lógica fuzzy. CBSF2010, Sorocaba (SP). *This is the paper that proposes the antigen recognition method presented in Chapter 4.*

2. Guilherme Costa Silva, Reinaldo M. Palhares, Walmir M. Caminhas: Algoritmo imunoinspirado nebuloso com agrupamento participativo aplicado ao problema se Deteccao e Diagnóstico de Falhas em Sistemas Dinâmicos. SBAI 2011, São João Del Rei (MG). *This paper has some further analysis of the monitoring-based method and introduces the clustering algorithm presented in Chapter 4.*

3. Guilherme Costa Silva, Reinaldo M. Palhares, Walmir M. Caminhas: Introducao ao algoritmo das células dendríticas no contexto de detecção de falhas em sistemas dinâmicos. CBA2012, Campina Grande (PB). *In this paper, there are some preliminary results that lead the analysis of the Chapter 5.*

4. Guilherme Costa Silva, Reinaldo M. Palhares, Walmir M. Caminhas: Classificador de padrões imunoinspirado baseado no modelo do reconhecimento nebuloso de antígenos, CBSF2012, Natal (RN). *In this paper, a classification method based on the method proposed in Chapter 4 is presented.*

Resumo Expandido

Introdução

Detectar e isolar Falhas são duas atividades que fazem parte do Gerenciamento de Eventos Anormais (AEM), um conjunto de tarefas que consiste em monitorar um sistema dinâmico apontando a ocorrência de anomalias e, com isso, evitando possíveis transtornos decorrente das mesmas. Entretanto, tais operações ainda são realizadas manualmente e a automatização destas será necessária com o objetivo de reduzir os problemas e melhorar a confiabilidade.

Nas últimas décadas, os Sistemas Imunoinspirados (AIS) têm sido empregados com sucesso em diversos problemas de computação e de engenharia, como a detecção de anomalias. Associando o problema da Detecção e Diagnóstico de Falhas e os princípios imunológicos, supõe-se que há diversos pontos em comum entre ambos. Isto possibilita o uso de diversas analogias e, assim, o desenvolvimento de diversas alternativas que possam oferecer resultados interessantes para a solução dos problemas.

Objetivos da Tese

Esta tese busca explorar as analogias imunológicas, demonstrando a relação entre os conceitos da imunologia e a aplicação na pesquisa sobre o problema de detecção e isolamento das falhas em sistemas dinâmicos e, através de novas contribuições e melhorias, viabilizar a resolução dos problemas. Especificamente, o trabalho busca atingir os seguintes objetivos.

1. Desenvolvimento de novas técnicas que aperfeiçoam métodos anteriormente desenvolvidos, como os algoritmos baseados na seleção negativa.

2. Facilitar o desenvolvimento de abordagens inspiradas em outros modelos imunológicos (como o Modelo do Perigo), melhorar a modelagem do conhecimento de especialistas, e explorar melhor o uso destes algoritmos aplicados ao problema de FDI.

3. Propor metodologias de isolamento das falhas capaz de distinguir diferentes tipos de falhas, uma vez detectadas pelo sistema imunoinspirado.

4. Aprofundar o estudo das inspirações imunológicas e apresentar a aplicabilidade das mesmas no problema de detecção de falhas.

Detecção e Diagnóstico de Falhas

O problema pode ser definido como um caso particular da Detecção de Anomalias, no qual um sistema dinâmico é monitorado e, eventualmente, a falha é detectada. Após a detecção, são extraídas informações como a localização (requerida para o isolamento), o tipo e o tamanho (requeridos para a identificação) e o tempo da falha, caracterizando a etapa de diagnóstico.

Grande parte dos sistemas de FDI empregam modelos de redundância, que consistem na estimação das variáveis de saída do sistema dinâmico para gerar o resíduo a partir da diferença entre o valor estimado e o valor obtido. Uma vez gerado, este resíduo é analisado pelo sistema de FDI para a tomada de decisão em relação ao status do sistema dinâmico, conforme os valores obtidos. A Figura 1 mostra um sistema de FDI conforme descrito.

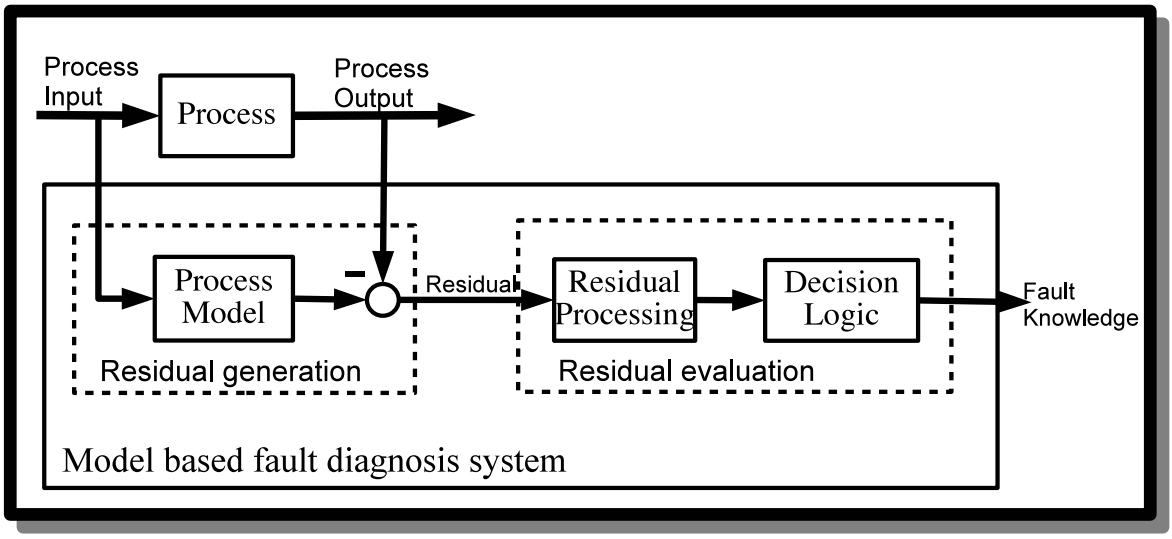


Fig. 1: Modelagem de um sistema dinâmico.

Um outro aspecto é a caracterização das falhas quanto à natureza temporal das mesmas, definidas a seguir:

1. Abruptas - Caracterizadas pela mudança abrupta e repentina do valor observado.

2. Incipientes - Caracterizadas pela mudança gradual e progressiva do valor observado. São falhas mais difíceis de detectar.

3. Intermitentes - Caracterizadas pela repetição de variações anormais no valor observado.

Nesta tese, os dois primeiros tipos são considerados. O problema de detecção e isolamento de falhas pode também ser definido como um problema de classificação, no qual são possíveis as seguintes situações, também utilizadas como fatores de desempenho:

- Alarme falsos (Dado de operação normal classificado como falha);
- Falha detectada e corretamente isolada;
- Falha detectada mas incorretamente isolada;
- Falha não detectada (Falha classificada como operação normal);
- e o Tempo de detecção da falha.

A Figura 2 ilustra o cenário descrito acima.

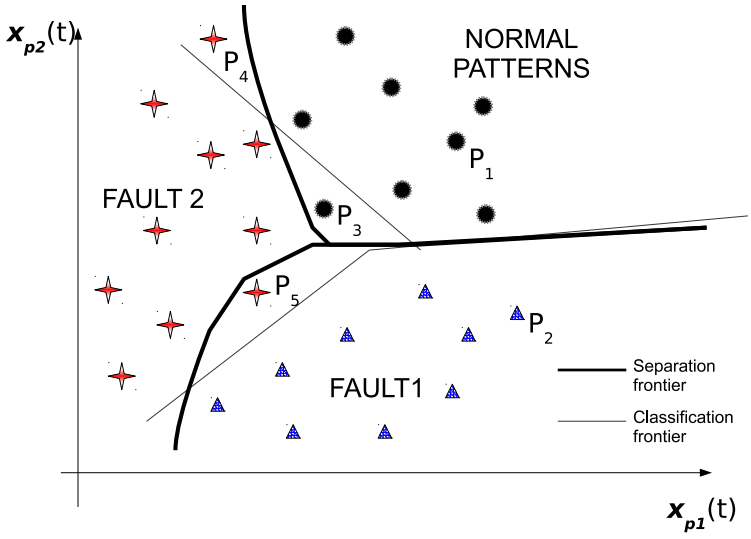


Fig. 2: Problema de Detecção e Isolamento de Falhas como um problema de classificação.

Nos casos estudados nesta tese, a etapa de diagnóstico é realizada após a detecção, e em todos os casos, é considerado que as falhas não são conhecidas a priori.

Sistemas Imunoinspirados

Os sistemas imunoinspirados são desenvolvidos com base em abstrações oriundas do sistema imune da biologia, cujas analogias servem como metáforas para o desenvolvimento de métodos e técnicas com a finalidade de prover soluções eficientes para problemas computacionais ou de engenharia. A linha de pesquisa foi consolidada como um método emergente de inteligência computacional e também como uma das principais linhas de pesquisa da computação natural.

Estes sistemas exploram vários tipos de analogias, que podem ser analisadas em pontos de vistas diferentes e de acordo com o contexto do problema em questão. As principais abordagens, assim como as principais aplicações estão listadas a seguir, dentre outros exemplos:

- Resposta Imune - Detecção de Anomalias / Novidades:
  - Discriminação *Self-Nonself*;
  - Modelo do Nonself Infeccioso;
  - Modelo do Perigo;
- Seleção Clonal - Otimização e Aprendizado;
- Rede Idiotípica - Agrupamento.

As primeiras abordagens foram inspiradas na discriminação self-nonself e aplicadas a problemas de segurança computacional. Os algoritmos então desenvolvidos possuem um mecanismo de geração de detectores inspirado na seleção negativa, que é análogo ao treinamento de algoritmos de aprendizado de máquina para uma classe, conforme ilustrado na Figura 3. Os detectores gerados são comparados com os demais dados (antígenos), exatamente como na etapa de teste de tais abordagens.

Após a consolidação da linha de pesquisa, uma segunda geração de algoritmos imunoinspirados foi introduzida com base nos outros modelos de resposta imune conhecidos. Dentre estes algoritmos estão o Algoritmo das Células Dendríticas (DCA), inspirado no modelo do perigo, e o Algoritmo de Receptores Toll-Like (TLR), inspirado principalmente no modelo do nonself infeccioso. Estes algoritmos têm sido aplicados a problemas de segurança computacional com resultados promissores. Ao longo da tese, estes algoritmos são estudados sob o ponto de vista da aplicação ao problema de FDI.

O modelo do nonself infeccioso considera a importância de um sinal característico para a detecção de uma anomalia, mesmo com o uso de dados de treinamento para a definição dos limites entre falhas e operação normal, representados pelo antígeno. Já o modelo do perigo é voltado

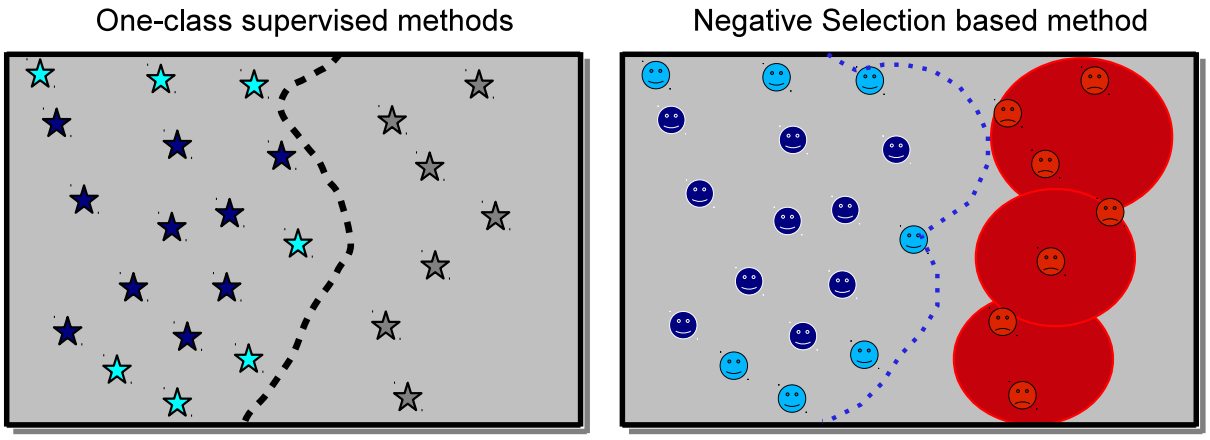


Fig. 3: Comparação entre o treinamento de algoritmos supervisionados e a geração de detectores nos algoritmos de seleção negativa.

para a definição e uso mais elaborado de tais conhecimentos, sendo o antígeno considerado apenas como um identificador para os sinais analisados.

Em termos computacionais, estes modelos são inerentemente complementares, definindo a necessidade de um mecanismo de treinamento (biologicamente representado pela seleção tímica) ou a necessidade do conhecimento de especialistas sobre o problema (biologicamente representado pela apoptose e necrose celular, segundo o modelo do perigo). Nessa representação transitória, quatro modelos são definidos a seguir.

- Discriminação *Self-Nonself*;
- *Self-Nonself* com sinal Co-estimulatório;
- Modelo do Nonself Infeccioso;
- Modelo do Perigo;

Estes modelos imunológicos possuem vínculos de transição entre os sistemas imunoinspirados, que podem servir de referência para o desenvolvimento de abordagens imunoinspiradas mais elaboradas.

Nesta tese, estes modelos são utilizados para entender como as abordagens imunoinspiradas funcionam no contexto do problema em questão, no caso o problema de detecção e isolamento de falhas (FDI).

Reconhecimento Antigênico Nebuloso

O método do Reconhecimento Antigênico Nebuloso foi proposto a partir de uma visão nebulosa da seleção ocorrida no timo, conforme a Discriminação *Self-Nonself*. Segundo esta visão, ilustrada na Figura 4, as células T que estiverem associadas com uma afinidade intermediária aos antígenos *Self* sofrem seleção positiva e sobrevivem ao processo. Isso indica que o objetivo deste processo é selecionar os clones reativos sub-ótimos com base nos padrões *Self*.

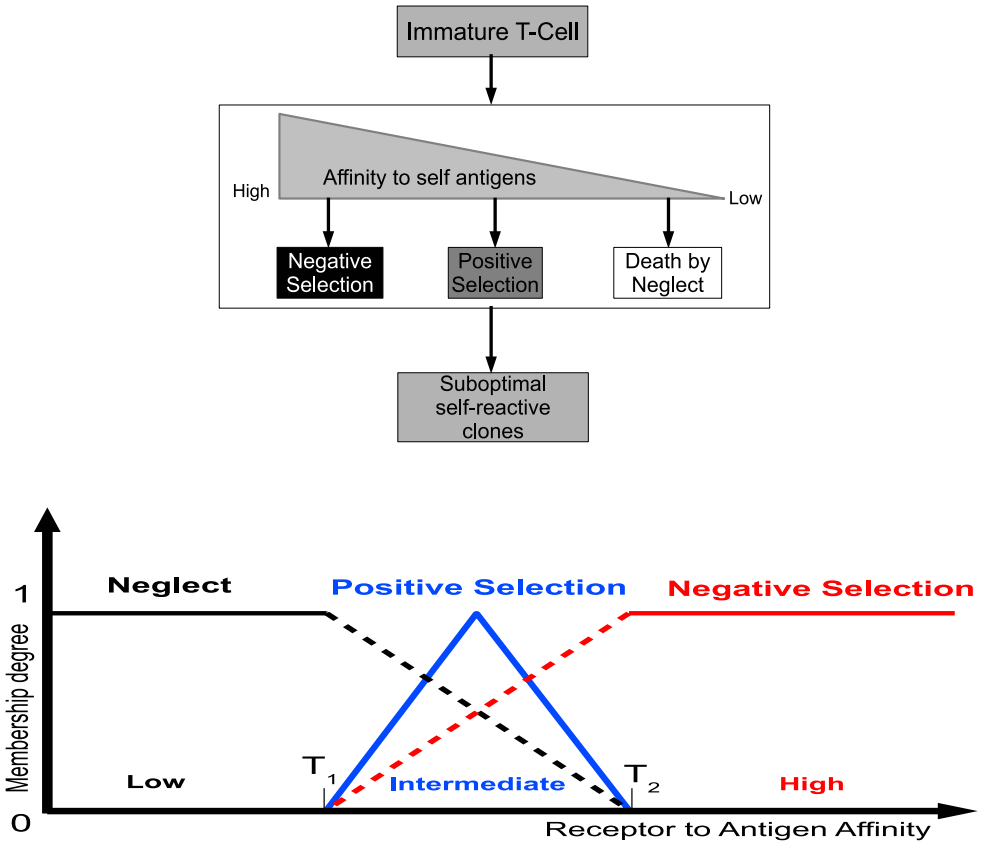


Fig. 4: Descrição do reconhecimento antigênico nebuloso e consequente maturação das células T.

A partir deste princípio, são considerados dois métodos que exploram estas ideias em um sistema de detecção de anomalias, conforme descrito a seguir:

1. Geração de Detectores - Usando qualquer algoritmo baseado na seleção negativa, o modelo nebuloso é aplicado para decidir se o detector será alocado ou não.

2. Monitoramento - Usando apenas os dados de treinamento e uma métrica de distância, classifica-se os dados de teste como 'normal' ou 'anomalia'.

O primeiro método reforça a geração dos detectores no espaço *nonself* através da regra nebulosa aplicada à distância entre o potencial detector e os dados *self* de treinamento. Na Tabela 1, as funções nebulosas estão representadas e definidas.

Tab. 1: Regras nebulosas do método de reconhecimento antigênico nebuloso baseado em geração de detectores.

	Rule	Feedback
1	Se *distancia* é `baixa`	Então *resposta* é `selecao_negativa`
2	Se *distancia* é `media`	Então *resposta* é `selecao_positiva`
3	If *distancia* é `alta`	Então *resposta* é `morte_or_negligencia`

Já o segundo método dispensa a etapa de geração dos detectores, uma vez que a distância entre o dado *self* de treinamento mais próximo e o dado de teste determina a classificação deste último. Porém, são necessárias apenas duas regras (das três consideradas no modelo) para o funcionamento deste método, conforme Tabela 2. Ambos os métodos estão ilustrados na Figura 5.

Tab. 2: Regras nebulosas do método de reconhecimento antigênico nebuloso baseado em monitoramento.

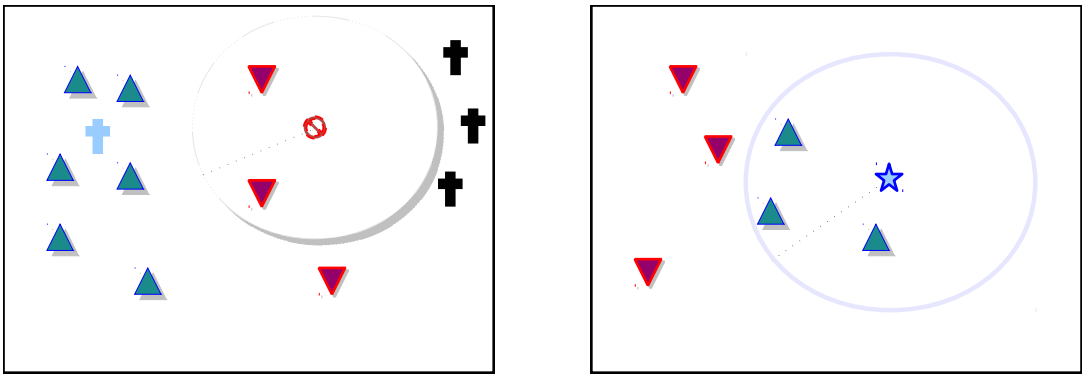
	Rule	Feedback
1	Se *distancia* é `baixa`	Então *resposta* é `selecao_negativa`
2	Se *distancia* é `alta`	Então *resposta* é `selecao_positiva`

Agrupamento Participativo

O algoritmo de agrupamento participativo é baseado na metodologia de aprendizado participativo, proposta na década de 90 como um mecanismo que define o funcionamento do aprendizado humano no contexto de revisão de conceitos aprendidos.

Este método de agrupamento consiste no emprego de um índice de compatibilidade aplicado aos grupos gerados e de um índice de alerta que é utilizado para medir a necessidade da geração de um novo grupo.

O algoritmo de agrupamento conta também com quatro variáveis de entrada: a taxa de aprendizado α para atualizações nos grupos, o tamanho de janela w que verifica mudanças no



(I) (II)

Fig. 5: Ilustração dos métodos propostos na tese: (I) Geração dos Detectores e (II) Monitoramento.

índice de compatibilidade, o nivel de significância λ, e o valor inicial da matriz de espalhamento Mtx, usada ao gerar os grupos.

O algoritmo consiste em gerar e verificar um conjunto de grupos **c** ao verificar a distância entre um ponto x_k e o centro do grupo c_g e através da matriz de espalhamento Mtx_g conforme (1).

$$D(x_k, c_g) = (x_k - c_g)(Mtx_g)^{-1}(x_k - c_g)' \tag{1}$$

Em (2), é calculado o índice de compatibilidade ρ_g de um grupo.

$$\rho_g = exp\{-\frac{1}{2}D(x_k, c_g)\} \tag{2}$$

Em seguida, o valor de ρ_g é comparado com um limiar $T\rho$, de acordo com o cálculo em (3).

$$T\rho = exp\{-\frac{1}{2}\chi^2_{n,\lambda}\} \tag{3}$$

Através de variáveis booleanas O_k que indicam violações no índice de compatibilidade ao longo do tempo, o índice de alerta a_g é calculado segundo uma distribuição de Bernoulli em (4). Em seguida, um limiar de alerta T_a é definido em (5).

$$a_g = \binom{w}{v}\lambda^v(1-\lambda)^{(v-w)}, v = 0, ..., w \tag{4}$$

$$T_a = 1 - \frac{\lambda}{w} \tag{5}$$

Conforme violações percebidas nos limiares, o algoritmo pode gerar novos grupos ou atu-

alizar um grupo existente. No segundo caso, o centro do grupo c_g e a matriz de espalhamento Mtx_g após o cálculo do fator G_g em (6).

$$G_g = \alpha(\rho_g{}^{1-a_g}) \tag{6}$$

$$c_g = c_g + G_g(x_k - c_g) \tag{7}$$

$$Mtx_g = (1 - G_g)(Mtx_g - G_g(x_k - c_g)'(x_k - c_g)) \tag{8}$$

Em alguns casos, pode haver redundância na geração de grupos, em (9), um mecanismo de comparação de grupos é utilizado para tratar este problema.

$$D(c_a, c_b) = (c_b - c_a)(M_a)^{-1}(c_b - c_a)' \tag{9}$$

E em seguida, um índice de compatibilidade é calculado entre os grupos a e b, que são unidos caso este índice seja maior que o limiar $T\rho$.

Este algoritmo de agrupamento é utilizado para o diagnóstico das falhas detectadas com o método de reconhecimento antigênico nebuloso, no estudo de caso do Motor de Corrente Contínua, apresentado nesta tese.

Estudo de caso - Motor de Corrente Contínua

O sistema de acionamento do motor de corrente contínua é uma simulação de um motor baseada em equações de estado elaboradas para o estudo das condições normais ou de falha. O sistema é composto por duas fontes de alimentação, conversores estáticos controlados, uma máquina de corrente contínua e uma carga mecânica, como ilustrado na Figura 6.

Neste benchmark, existem onze falhas que podem ser simuladas de acordo com as possíveis situações ocorridas em um motor, influenciando as variáveis observadas. Destas, sete são avaliadas neste estudo de caso, conforme a Tabela 3. Neste estudo de caso, os algoritmos de reconhecimento antigênico nebuloso e o algoritmo de agrupamento participativo são aplicados.

Para todos os testes, considera-se $1000ms$ de dados de treinamento (operação normal) e $3000ms$ de teste (normal e/ou falha), para o motor em regime, sem ruídos e sem uso de modelos de redundância. Todos os resultados são apresentados em termos de um problema de classificação.

Com o método de geração de detectores, utiliza-se os limiares $T1 = 0.15$ e $T2 = 0.95$, o

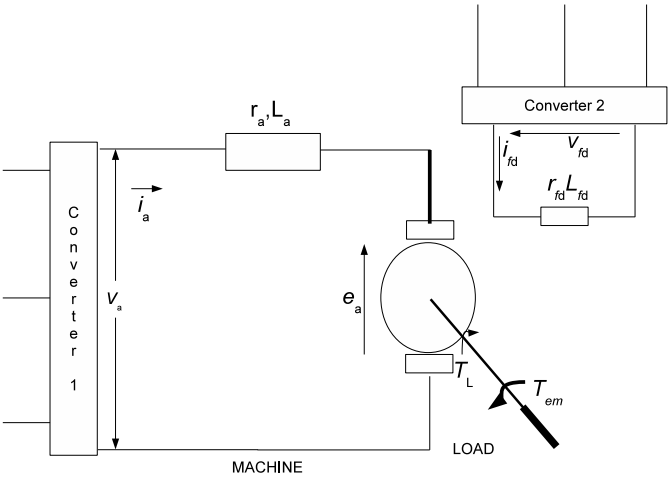


Fig. 6: Reprentação do benhcmark do motor de corrente contínua.

Tab. 3: Falhas do motor de corrente contínua.

Índice da falha	Tipo de falha
1	Desconexão do conversor da armadura
2	Desconexão do conversor de campo
3	Curto circuito no conversor da armadura
4	Curto circuito no conversor de campo
9	Falha no sensor de armadura
10	Falha no sensor de campo
11	Falha no sensor de velocidade

algoritmo utilizado é o V-Detector,com a cobertura desejada de $97,5\%$, e o critério de parada após 250 detectores alocados ou 100 tentativas. Os resultados estão disponíveis na Tabela 4.

Para o método de monitoramento, adota-se um limiar $thr = 0.95$. Os resultados estão disponíveis na Tabela 5.

Ambos os métodos apresentaram resultados interessantes, principalmente a abordagem baseada em monitoramento, na qual foi possível distinguir os dados normais dos dados de falha.

A definição do método de monitoramento pode ser uma boa alternativa para os problemas de custo computacional dos demais algoritmos baseados na seleção negativa, uma vez que dispensa a geração de detectores e a posterior comparação dos dados de teste com os mesmos.

Em seguida, foram feitos os experimentos com o algoritmo de agrupamento participativo, com o objetivo de isolar as falhas encontradas. A taxa de aprendizado foi definida como $\alpha = 0.1$, enquanto os valores de w e de λ variam conforme análise paramétrica. O melhor resultado foi

Tab. 4: Resultados com o algoritmo de geração de detectores.

Cenário	Pontos detectados	Atraso	FP	FN
Normal	0	-	0%	0%
Falha 1	2001	0	0%	0%
Falha 2	2001	0	0%	0%
Falha 3	2001	0	0%	0%
Falha 4	1994	6	0%	3%
Falha 9	2001	0	0%	0%
Falha 10	2001	0	0%	0%
Falha 11	2001	0	0%	0%

	Detectores Usados	Detectores Inúteis	Detectores Descartados
Número	83	17	0

Tab. 5: Resultados com o algoritmo de monitoramento.

Cenário	Pontos detectados	Atraso	FP	FN
Normal	0	-	0%	0%
Falha 1	2000	0	0%	0%
Falha 2	2000	0	0%	0%
Falha 3	2000	0	0%	0%
Falha 4	2000	0	0%	0%
Falha 9	2000	0	0%	0%
Falha 10	2000	0	0%	0%
Falha 11	2000	0	0%	0%

o obtido para $w = 3000$ e $\lambda = 0.0005$, conforme a Tabela 6.

O agrupamento participativo é uma alternativa interessante, porém com uma sensibilidade paramétrica alta, no sentido de influenciar na geração dos grupos conforme variação nos parâmetros escolhidos, seja na distinção entre grupos, seja no número de grupos gerados.

Algoritmos de Segunda Geração

Nesta tese, mais dois algoritmos são apresentados como alternativas para detecção de falhas em sistemas dinâmicos: o Algoritmo das Células Dendríticas (DCA) e o Algoritmo dos Receptores Toll-Like (TLR), com aplicabilidade até então desconhecida ao problema de FDI.

Tab. 6: Resultados para $w = 3000$ e $\lambda = 0.0005$.

Cenário	Acertos	Erros	Grupos
Normal	4000	0	1 (0)
Falha 1	2000	0	1 (1)
Falha 2	2000	0	1 (2)
Falha 3	2000	0	1 (3)
Falha 4	2000	0	1 (4)

Estes métodos, porém, requerem o uso de um conhecimento baseado de especialistas sobre a aplicação, que neste contexto são representados pelos sinais. Estes sinais são os responsãveis pela emissão do alarme nestes métodos, enquanto o antígeno é o dado a ser classificado por estes algoritmos.

No problema de FDI, este fator pode ser considerado um desafio, uma vez que o conhecimento sobre o sistema dinâmico nem sempre está disponvel ou pode ser inferido no mesmo, pois em muitos sistemas dinâmicos, os dados sÃčo limitados. Além disso, tais dados do sistema dinÃćmico muitas vezes possuem características como ruídos e perturbações por exemplo.

Os modelos de redundância, definidos para gerar o resíduo utilizado na comparação com a saída do sistema, podem ser interpretados pelos métodos como os sinais requeridos para a detecção da falha. Outros testes foram feitos, considerando por exemplo a diferença entre dados entre instantes de tempo, porém, em sistemas não lineares ou com ruídos consideráveis, estes dados podem corromper a análise, gerando alarmes falsos.

Nestes algoritmos, o antígeno foi definido como sendo a saída do sistema dinâmico, o dado a ser classificado.

Algoritmo das Células Dendríticas

O DCA funciona através da correlação entre os sinais processados, que representam o comportamento da aplicação, e os antígenos, coletados para serem classificados e associados ao contexto relativo aos sinais analisados. As células dendríticas são os agentes que coletam os antígenos e estão expostas às informações representadas pelos sinais, coletadas de forma cumulativa.

Os sinais possuem quatro categorias na formulação original do algoritmo, sendo que duas delas, o sinal apoptótico (SS) que evidencia o comportamento normal do sistema e o sinal necrótico (DS) que evidencia uma possível anomalia, são consideradas nesta tese, considerando a versão determinística do algoritmo. A partir destes sinais, são gerados outros dois sinais, um sinal migratório CSM, calculado em (10), que representa o tempo de vida da célula antes de ser analisada, e o sinal resultante K, calculado em (11), cujo valor revela o contexto da

aplicação, conforme a célula e os antígenos analisados. Todos os passos acima são resumidos no fluxograma da Figura 7.

$$CSM = DS + SS \tag{10}$$

$$K = 2DS - SS \tag{11}$$

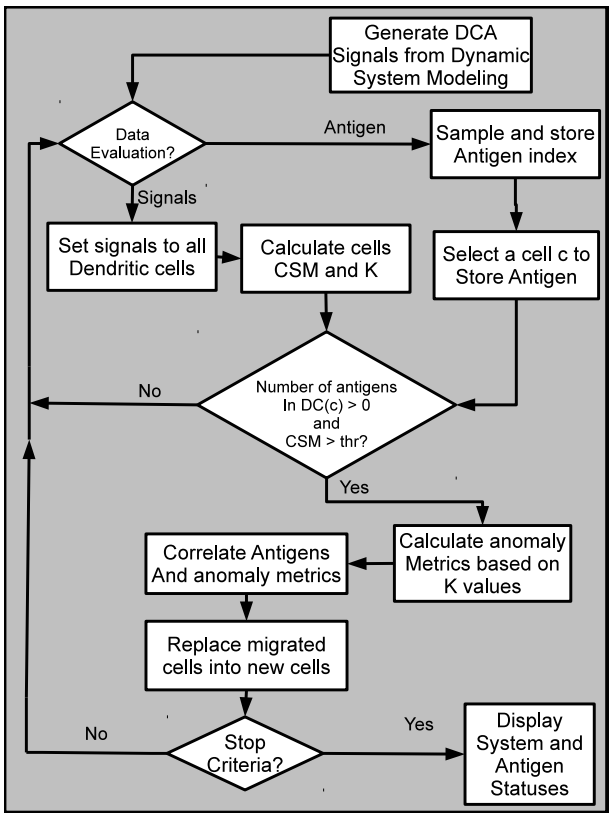


Fig. 7: Fluxograma que descreve os principais passos do DCA.

Para calcular SS e DS, é utilizado o seguinte conjunto de equações em (12) e (13).

$$\begin{aligned} r_{(k)} &= \frac{\sum_{i=1}^{N}(y_{(k,i)} - \hat{y}_{(k,i)})^2}{N} \\ j_o &= max(1, k - w) \\ SS_{(k)} &= \frac{\sum_{j=j_o}^{k} r(j)}{k - j_o} \end{aligned} \tag{12}$$

$$DS_{(k)} = \sum_{i=1}^{N}(max(r_{(k)}, w) - min(r_{(k)}, w)) \tag{13}$$

Sendo os sinais normalizados conforme as regras em (14) e (15).

$$DS'_{(k)} = min(0, max(100DS_{(k)}, 10)) \tag{14}$$

$$SS'_{(k)} = max(0, min(1 - 10SS_{(k)}, 1)) * 5 \tag{15}$$

Em seguida, métricas são utilizadas para determinar o status da aplicação de acordo com os valores obtidos. Nesta tese foram propostos duas novas métricas para serem usadas no DCA aplicado ao problema de detecção de falhas: o Alarme de Falha Ciente do Contexto Celular ($CCAFA$) usado para a emissão do alarme e calculado conforme (16), e o Índice Antigênico de Diferenciacção da Falha (AIFD), usado para medir a associacção dos antígenos ao contexto do sistema e calculado em (17).

$$\begin{aligned} \sum_{DC} G_K^+ &= \frac{\sum_{DC} K^+}{\sum_{DC} M} \\ \sum_{DC} G_K^- &= \frac{\sum_{DC} K^-}{\sum_{DC} Sm} \\ f(\phi) &= 1 - e^{-\phi} \\ CCAFA &= f(G_K^+) - f(G_K^-) \end{aligned} \tag{16}$$

$$AIFD(a) = \begin{cases} Jaccard(a, M) * \sum(K(a)), & CCAFA > thr \\ 0, & \text{Caso contrário} \end{cases} \tag{17}$$

Algoritmo dos Receptores Toll-Like

O Algoritmo TLR estruturado possui um mecanismo de treinamento no qual são modelados tanto o espaço de classificação do antígeno, relativo à discriminação *self-nonself*, quanto as regras para definições dos sinais processados pelo algoritmo. De forma semelhante ao DCA, células são utilizadas para o processamento do algoritmo, porém, com um processamento muito diferente.

Existe apenas um sinal a ser avaliado, que é relativo às regras construídas durante o treinamento. Neste caso a categorização é binária, relativa ao sinal estar de acordo com as regras processadas . O valor 1 provoca a maturação da célula, enquanto o valor 0, persistente até um determinado limiar, causa semimaturação da célula. Para a ativação do alarme, a célula

deve sofrer maturação e o antígeno deve ser classificado como *nonself*, qualquer outro resultado classifica o status da aplicação como normal. Estes passos são resumidos no Fluxograma da Figura 8.

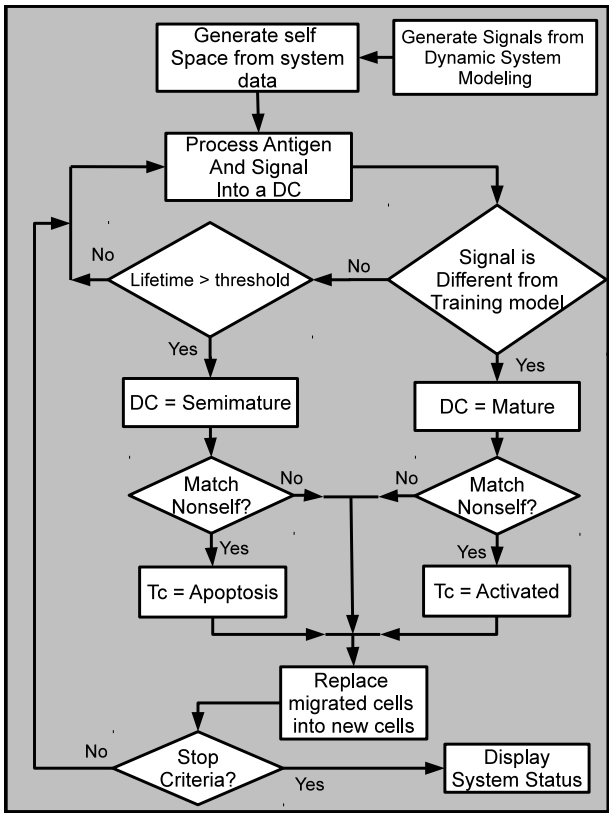


Fig. 8: Fluxograma que descreve os principais passos do algoritmo TLR.

O TLR, assim como o DCA, são aplicados ao estudo de caso do benchmark DAMADICS, com o objetivo de verificar o desempenho dos métodos em diferentes tipos de falhas e aplicabilidade destes ao problema de detecção de falhas.

Estudo de Caso - DAMADICS

O DAMADICS é um benchmark de um processo industrial que consiste em simular as condições da operação de uma fábrica polonesa de açúcar. São obtidos como saída as informações sobre o status de atuadores do sistema, de acordo com a Figura 9. O benchmark contém 19 falhas que podem ser simuladas, destas, seis são estudadas no trabalho conforme descrição da Tabela 7, tanto nas formas abruptas quanto incipientes, quando houver.

Para este estudo de caso, além dos dois algoritmos estudados neste trabalho, outras duas abordagens são usadas para o estudo de caso. Uma delas consiste na modelagem de um método

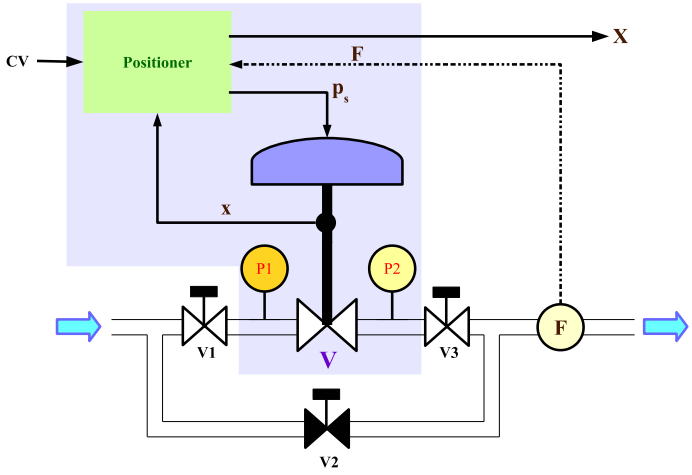


Fig. 9: Descrição do benchmark DAMADICS.

Tab. 7: Falhas simuladas no estudo de caso do DAMADICS.

Código	Localização	Descrição
f0	-	Operação Normal
f1	Válvula de Controle	Entupimento
f7	Válvula de Controle	Evaporação ou Fluxo crítico
f13	Posicionador	Falha no sensor de posicionamento da haste
f15	Posicionador	Falha na mola do posicionador
f17	Geral ou Externa	Variação inesperada de pressão ao longo da válvula
f19	Geral ou Externa	Falha no sensor de fluxo

inspirado no modelo do perigo, desenvolvido anteriormente para o problema de detecccão de falhas e que utiliza apenas resíduos como sinais, o método é utilizado neste trabalho tanto para análise quanto para comparaccão. A outra abordagem consiste no classificador SVM de uma classe com pré processamento realizado pelo PCA, usada apenas para comparaccões com os outros três métodos.

Para o Algoritmo das Células Dendríticas, utiliza-se o número de 25 células, que podem armazenar até 10 antígenos, um tempo de vida de aproximadamente 10 avaliações e o tempo de Amostragem na faixa de valores de $T_s = \{120, 60, 30, 2\}$.

No Algoritmo dos Receptores Toll-Like, são usadas 20 células APC, tempo de vida de 5 avaliações, e com possibilidade de usar dois algoritmos para avaliar o espa.ço self: o reconhecimento antigênico nebuloso ou o SVM de uma classe. Além disso, o antígeno pode ser avaliado

em uma janela móvel na faixa de valores de $W = \{10, 5, 1\}$.

O Algoritmo baseado no Modelo do Perigo usa entradas e saídas do modelo nebuloso normalizadas no intervalo $[0, 1]$ conforme (18), e o limiar de alarme imune correspondente a função de estresse do sistema. Sendo que $rmax = 80std(r_{tr})$.

$$\bar{SS}(t) = \begin{cases} 1, & r_{ts}(t) > rmax \\ \frac{r_{ts}(t) - rmin}{rmax - rmin}, & \text{Caso contrário} \end{cases} \tag{18}$$

Para o SVM de uma classe com pré processamento usando PCA, usa-se $\mu = 0.0000028$, o kernel de base radial e um índice de tolerância $AT = 2$, para minimizar alarmes falsos ocorridos previamente.

Nos testes realizados com o DCA (Tabela 8, todas as falhas foram detectadas na maioria dos casos. O algoritmo não apresentou alarmes falsos e o tempo entre o instante de ocorrência da falha e a detecção foi relativamente baixo. As falhas incipientes foram detectadas, porém apenas uma delas apresentou um baixo índice de atraso. O algoritmo apresenta um custo computacional consideravelmente baixo, mas com um pré processamento considerável.

Tab. 8: Detectando falhas com o DCA, com $T_s = 2$.

Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(TS)$
`f0`	No fault	-	0%	-
`f1`	ASm	99.1667%	0%	2.4349
	AMe	100%	0%	2.4771
	ALa	100%	0%	2.2715
`f7`	ASm	100%	0%	1.5479
	AMe	100%	0%	1.5219
	ALa	100%	0%	1.5376
`f13`	ASm	99.1667%	0%	1.8702
	AMe	100%	0%	1.6303
	ALa	99.1667%	0%	2.4545
	Inc	100%	0%	3.3937
`f15`	ALa	97.5%	0%	19.2597
`f17`	ALa	100%	0%	1.5631

Continued on next page

Tab. 8 – continued from previous page				
Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(TS)$
	Inc	97.5%	0%	19.2597
f19	ASm	100%	0%	3.9451
	AMe	100%	0%	2.2386
	ALa	100%	0%	1.9204

Nos testes realizados com o Algoritmo TLR, a maioria das falhas foram detectadas, apenas uma delas o algoritmo não foi capaz de detectar (f19 de baixa intensidade). O algoritmo também não apresentou alarmes falsos. O tempo de resposta à falha foi um pouco maior que o do DCA na maior parte dos casos. Quanto ao uso do algoritmo SVM (Tabela 9) em relação ao NSA fuzzy (Tabela 10) não houve uma diferença significantemente grande. O TLR possui um custo computacional considerável devido às avaliações necessárias.

Tab. 9: Detectando falhas com o TLR usando o SVM para o espaço Nonself e $W = 1$.

Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
f0	No fault	-	0%	-
f1	ASm	99.1667%	0%	112.9664
	AMe	100%	0%	42.9667
	ALa	100%	0%	99.275
f7	ASm	100%	0%	1.3
	AMe	100%	0%	1.3167
	ALa	100%	0%	1.2917
f13	ASm	99.1667%	0%	24.3866
	AMe	100%	0%	12.7417
	ALa	99.1667%	0%	44.437
	Inc	100%	0%	157.8917
f15	ALa	100%	0%	20.5333
f17	ALa	100%	0%	1.2667
	Inc	97.5%	0%	1608.2393
	ASm	0%	0%	-
f19	Continued on next page			

Tab. 9 – continued from previous page				
Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
	AMe	96.6667%	0%	270.1379
	ALa	100%	0%	20.9917

Tab. 10: Detectando falhas com o TLR usando o Reconhecimento Antigênico Fuzzy para o espaço Nonself e $W = 1$.

Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
`f0`	No fault	-	0%	-
`f1`	ASm	99.1667%	0%	112.9244
	AMe	100%	0%	42.8833
	ALa	100%	0%	99.3417
`f7`	ASm	100%	0%	1.325
	AMe	100%	0%	1.2333
	ALa	100%	0%	1.3
`f13`	ASm	99.1667%	0%	24.437
	AMe	100%	0%	12.7833
	ALa	99.1667%	0%	44.4706
	Inc	100%	0%	157.8667
`f15`	ALa	100%	0%	20.5333
`f17`	ALa	100%	0%	1.2583
	Inc	97.5%	0%	1608.3077
`f19`	ASm	0%	0%	-
	AMe	96.6667%	0%	270.2069
	ALa	100%	0%	21.1583

Nos testes realizados com o algoritmo baseado no modelo do perigo (Tabela 11), a maioria das falhas foram detectadas, com índices menores de acertos em algumas falhas, como nos outros dois algoritmos, sem alarmes falsos. O tempo de resposta à falha foi consideravelmente grande. A maior vantagem desta abordagem se deve a seu custo computacional baixo em relação às demais abordagens.

Tab. 11: Detectando falhas com o método baseado no Modelo do Perigo.

Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
f0	No fault	-	0%	-
f1	ASm	99.1667%	0%	380.46
	AMe	99.1667%	0%	432.16
	ALa	95.85%	0%	430.96
f7	ASm	99.1667%	0%	132.03
	AMe	100%	0%	118.89
	ALa	100%	0%	136.8
f13	ASm	96.6667%	0%	287.02
	AMe	100%	0%	225.03
	ALa	95.8333%	0%	452.85
	Inc	99.1667%	0%	365.56
f15	ALa	97.50%	0%	351.3846
f17	ALa	99.1667%	0%	139.1765
	Inc	99.1667%	0%	1297.4
f19	ASm	96.6667%	0%	2326.2
	AMe	95%	0%	820.44
	ALa	95.85%	0%	464.36

Nos testes realizados com o SVM de uma classe (Tabela 12), a taxa de detecção foi relativamente baixa e houve alarmes falsos em todos os testes. O tempo de resposta à falha foi muito alto, mostrando que os algoritmos imunoinspirados obtiveram um desempenho maior em relação a esta estratégia.

Tab. 12: Detectando falhas com o SVM de uma classe, e com pré processamento realizado pelo PCA.

Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
f0	No fault	0%	42%	0
f1	ASm	90.8333%	9.1667%	44.6606
	AMe	0%	10.8333%	0

Continued on next page

Tab. 12 – continued from previous page				
Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
	ALa	88.3333%	11.6667%	37.5566
f7	ASm	86.6667%	13.3333%	2.7885
	AMe	86.6667%	13.3333%	2.8942
	ALa	82.5%	17.5%	2.899
f13	ASm	45.8333%	15%	12947.0182
	AMe	43.3333%	13.3333%	14046.4231
	ALa	0%	15%	0
	Inc	87.5%	10.8333%	735.3905
f15	ALa	86.6667%	13.3333%	13.6827
f17	ALa	89.1667%	10.8333%	2.972
	Inc	90%	10%	380.0093
f19	ASm	23.3333%	13.3333%	23389.3214
	AMe	1.6667%	13.3333%	29916
	ALa	0.83333%	13.3333%	39102

Para isolamento de falhas utilizando o DCA, foi considerada uma similaridade máxima de $D < 0.4$ entre os pontos de falha, usando a distância euclideana, conforme aplicação do algoritmo, todos os antígenos com índice $AIFD > 0$ são armazenados e marcados para avaliação.

Com este procedimento, os dados de antígenos são agrupados e medidos mutuamente quanto a taxas de distinguibilidade (Tabela 13) e de ambiguidade (Tabela 14). Na primeira, quanto mais distante de 0, mais distintas é a classe/falha detectada. Já na segunda, a ambiguidade é menor quando os valores são próximos de 0.

Os resultados mostram que o DCA consegue isolar algumas falhas através da correlação antigênica seguido do uso de uma métrica de distinção.

Tais resultados obtidos são promissores para estes algoritmos, embora a exigência de modelos esteja evidente na aplicação destas técnicas, tornando-se uma condição essencial para o uso destas no problema, tais abordagens podem prover recursos interessantes para a detecção das falhas.

Tab. 13: Valores de Taxa de Distinguibilidade de Distância para os antígenos coletados pelo DCA.

	f1	f7	f13	f15	f17	f19
f1	0	0.9074	0.7437	1.3932	0.7168	1.8803
f7	0.9074	0	1.2187	1.7834	1.2938	1.3155
f13	0.7437	1.2187	0	1.1213	0.6342	1.0069
f15	1.3932	1.7834	1.1213	0	1.2237	1.1003
f17	0.7168	1.2938	0.6342	1.2237	0	0.7284
f19	1.8803	1.3155	1.0069	1.1003	0.7284	0

Tab. 14: Valores de Taxa de Ambiguidade para os antígenos coletados pelo DCA.

	f1	f7	f13	f15	f17	f19
f1	1	0.0202	0.0909	0	0.0241	0
f7	0	1	0	0.0309	0	0
f13	0	0.0349	1	0.0844	0.1530	0
f15	0	0.0268	0	1	0.0057	0
f17	0	0.0419	0	0.1057	1	0
f19	0	0.0132	0.0909	0	0.0494	1

Chapter 1

Introduction

This chapter presents the main aspects of this Thesis: motivations - describing the relevance of the problem in question - objectives, methodologies, contributions and its structure.

1.1 Motivation and Relevance

The Abnormal Events Management (AEM) in real-time processes provides a set of tasks, which includes detection, diagnosis and anomalies correction. These tasks should be effectively observed and planned. The AEM is useful since the anomaly early detection allows a high degree of reliability to operate the systems, avoiding any downtime, material losses, fall in production quality and even accidents involving humans.

According to [Venkatasubramanian et al., 2003a], 7 out of 10 accidents are caused by human error that are usually ignored or misdetected. The need for automation of these processes comes from their size and complexity due to the fact, that these tasks has been performed manually. For these reasons presented, the demand for such systems that provides automatic management of abnormal events increases.

In order to reduce these problems and increase the reliability, the Fault Detection and Isolation systems (FDI), also termed as Fault Detection and Diagnostic Systems (FDD) have been widely used to automate the processes of AEM. Several principles and methodologies are discussed in works as [de Almeida et al., 2010, de Almeida et al., 2011, D'Angelo et al., 2011]. Definitions and terminology used are considered in [Isermann, 2011].

Artificial Immune Systems (AIS) is a research field, part of Computational Intelligence and Nature-inspired Computing that emerged in the mid 1980s and has grown in recent times, offering the analogy with the body's defense system as an alternative that seeks to provide solutions to different categories of computational and engineering problems, such as anomaly

detection, optimization problems, clustering, pattern recognition, among others.

The biological immune system and the problem of Fault Detection and Isolation have many points in common that can be exploited, such as the need of differentiation and adaptability in the case of unknown fault detection. These functions, among others, may provide some powerful tools that can cope with FDI applications accordingly.

AIS research has increased with works such as those in [De Castro and Timmis, 2002], which provides various methodologies inspired by immunology. It is considered that FDI problems have features that AIS approaches can deal with, and after the research in [Forrest et al., 1994], most approaches have presented interesting results with some anomaly detection problems.

Some new initiatives related to the development of immune-inspired systems were advocated in [Aickelin and Cayzer, 2002] by proposing the Danger Model as a more suited alternative to the problem of detecting anomalies. The subsequent work in [Aickelin et al., 2003] demonstrates how to develop such systems applied to computer security.

Fault detection tasks have been addressed in works such as [Guzella et al., 2007], based on the dynamics of regulatory T cells; [de Almeida et al., 2010,de Almeida et al., 2010,de Almeida et al., 2011], with approaches based on Negative Selection, Danger Model and NK cells, respectively.

This thesis aim at exploring in depth some immunological analogies, showing the relationship between the concepts in immunology and application in the detection of faults in dynamical systems and, through new contributions and enhancements, provide new ways of solving FDI problems.

1.2 Objectives and Methodology

1.2.1 General Purposes

The purpose of this work is to review and improve immunological analogies to study the Fault Detection and Isolation (FDI) application since such systems have many points in common with the biological immune system. The main objective of FDI systems is the recognition of anomalies of a process component, or even the process itself through its monitoring. Fault detection is the first task of the system, the next step is its proper isolation.

1.2.2 Specific Objectives

1. Development of new fault detection approaches, which improve previously developed methods, such as Negative Selection based approaches.

2. To facilitate the development of Danger model-based approaches, improving the expert modeling considered, to better explore the use of these algorithms applied to this problem.

3. To propose Fault Isolation methodologies capable of distinguish different types of faults, once a fault is detected by the AIS approach.

4. To deepen immunological models and to present the applicability of all models to Fault Detection applications.

1.2.3 Approaches used in the thesis

One of proposed approaches for fault detection makes use of an approach based on a fuzzy model of antigen recognition (*Self-nonself* Discrimination), which measures recognition of anomalies across the distance between the data and the *Self* space, as two models:

1. Detector generator-based model. In this model, detectors generated in the *Self* space (normal patterns) suffer negative selection, the detectors generated away from the other regions are eliminated by neglect. The detectors generated in the *nonself* region (outliers) remain through Positive Selection.

2. Monitoring-based model. In this case, there is no generation of detectors, since the fuzzy system which defines the region where the data are entered.

The proposed method, unlike other techniques, sets the fuzzy model of *self-nonself* discrimination.

Other methodologies define the inspiration of new FDI systems inspired by the Infectious Nonself and Danger Models. Some of these approaches are listed below:

- The Dendritic Cell algorithm (DCA) from [Greensmith and Aickelin, 2008];
- The Toll-like Receptors (TLR) algorithm from [Nejad et al., 2012];
- The Danger Model approach in [de Almeida et al., 2010].

However, as Danger model inspired still has several issues related to the context of the algorithm, data monitoring will require an expert modeling so that the system operates correctly.

Most of these approaches are based on a previously proposed algorithm, such as most NSA approaches. The CSPRA, proposed in [Yu and Dasgupta, 2008] is based on the original NSA, but is based on the INS model, and the Multioperational Negative Selection Algorithm (MO-NSA), proposed in [de Almeida et al., 2010] is based on the V-detector algorithm. The

Deterministic DCA, proposed in [Greensmith and Aickelin, 2008], and the Structured TLR algorithm, proposed in [Nejad et al., 2012], were proposed as improvements on DCA and TLR, respectively. A schematic preview of all presented and related approaches based on their origin is depicted in Figure 1.1.

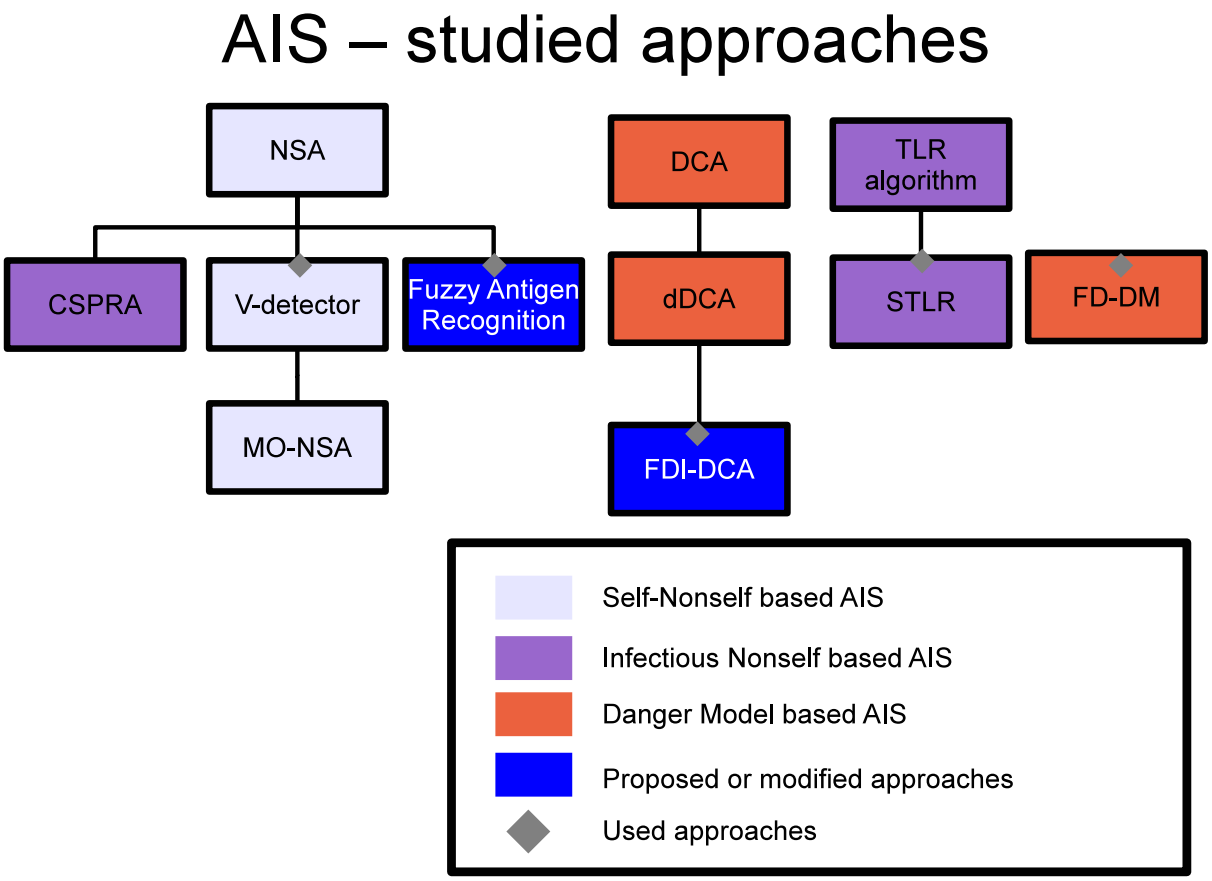


Fig. 1.1: Preview of all studied AIS approaches and their origins and immunological models of inspiration.

1.3 Thesis Contributions

This study has been proposed to achieve the following contributions:

- Some new concepts, among them the transitional link between immune response models (Self-nonself, Infectious Nonself and Danger-based) and their features related to applications. These concepts aim at ease the development and adoption of immune inspired techniques, according to the application focus and type of data used. In literature, immune response models have inspired some detection methods, but without considering

how far their features should be properly exploited. In [Aickelin and Cayzer, 2002], a brief study was done in favor of proposing novel approaches based on the Danger Model.

- Analysis of expert knowledge gathering in the context of Fault Detection in Dynamic Systems, which identifies each process and then application of AIS approaches. Some immune-inspired models rely on expert knowledge, and since most FDI systems use redundancy models to provide residuals, this work presents how residuals can be combined to immune-inspired methods and provide decision. This was done in [de Almeida et al., 2010], but this analysis was not the focus of the authors' research.

- A New Negative Selection model based on Fuzzy Antigen Recognition. Differently from most negative selection-based approaches, which are mostly based on detectors generation, this model is inspired on the theory of sub-optimal antigen recognition to the immune response, and the algorithm focuses on the decision making process regarding the detection of an anomaly. This mechanism, as it can be noticed along this work, may provide an interesting training mechanism for some algorithms. In this model, two approaches were considered, as follows:

  - An extension of detector generation-based Negative Selection algorithms, in which the decision process defines where anomaly detectors can be generated.
  - Monitoring algorithm based on Self data (training) analysis, as the decision process defines the classification of the data as a normal or anomaly process.

- A study on algorithms inspired in other immunological models that employ mechanisms of innate immunity and analyzing the important fundamentals and basic considerations for their use in FDI applications. Some approaches, such as the Dendritic Cell Algorithm [Greensmith, 2007] and the Toll-Like Receptors [Twycross et al., 2010] were developed for other anomaly detection problems, such as IDS, but their applicability to FDI Problems has not been widely studied in literature as well as their performance in this class of problems are still unknown.

- Some improvements in dendritic cell algorithm-based approaches and their application to FDI problems, as well as in other algorithms, the Toll-Like Receptor based algorithm. Since these kind of techniques were not initially developed for FDI problems, these improvements were proposed in order to provide a suitable detection for these algorithms. A comparison among these techniques, the method developed in [de Almeida et al., 2010], and some other machine learning were also considered, as well as a fault isolation mechanism for DCA.

1.4 Text Organization

This Thesis is organized as follows: Chapter 2 presents the most important aspects of the problem of Fault Detection and Isolation, main application of the thesis. In Chapter 3, a survey about AIS, with description of the state-of-the-art, methodologies, applications and also a brief description of each immunological model with their transitional link, are presented and discussed. In Chapter 4, the negative selection algorithm is discussed and the fuzzy model of antigen recognition is introduced, as well as their respective results applied to the Direct Current motor (DC Motor) benchmark proposed in [Caminhas, 1997]. In Chapter 5, systems based on other immunological models (infectious nonself and danger model) are presented, as well as their application to Fault Detection, the discussion about expert knowledge in the problem, and some improvements to each algorithm in order to provide a proper solution to FDI problems, in particular the DAMADICS benchmark, which is the main application in this chapter. Finally, the Chapter 6 presents the concluding remarks and contributions made in this work, as well as further and ongoing research still to be considered.

Chapter 2

Fault Detection and Diagnosis in Dynamic Systems

2.1 Introduction

Fault detection in dynamic systems is a particular case of anomaly detection, which according to [Chandola et al., 2009], consists of the activity or task to find the data, patterns that do not match the expected behavior. These standards are defined as anomalies, outliers, exceptions, among other terms. The anomaly detection is applicable to various contexts and domains, such as intrusion detection in computer networks, fraud detection, fault detection, lie detection, among other applications.

Developing these approaches is an ongoing challenge in the literature, considering various aspects defined in [Chandola et al., 2009] or inferred during the research, such as:

- the definition of normal behavior, due to the uncertainties encountered in establishing boundaries between patterns of normality and abnormality;
- the existence of malicious actions that make such behaviors as normal to the system;
- the notion of normal behaviors may change with time;
- differences between the exact notion of anomaly in various application domains;
- availability of training data;
- existence of factors like noise, which complicate the analysis techniques;
- uncertainties or inaccuracies in the existing models built for detection, which can lead to errors in the analysis (False Positives, and False Negatives);

- many techniques do not contextualize the scope of the considered problem.

The definition of abnormality is closely related to the context of novelty detection, which according to [Markou and Singh, 2003], aims identify data or signals considered novel or unknown, not contextualized by a learning machine during the training phase. In [Steinwart et al., 2005], both are similar, as anomaly can be seen as something different from what is normal or not in accordance with the standards and therefore is not considered satisfactory.[1]

The context of fault detection systems involves the monitoring of a dynamic system. In addition to this, diagnosis task should be performed, which generally considers some prior knowledge, the obtaining of these is often a difficult task to be performed. The diagnosis is usually made during or after the detection of a fault, considering some relevant information, as the type, location and time of a fault. A Fault Detection and Diagnosis system, according to [Gao and Dai, 2013], may detect the occurrence of faults as soon as possible and identify location and type of these faults with the best accuracy. These systems are a particular case of anomaly detection systems, since their goal is, once a fault is detected, to verify each fault behavior, identify them and then classify the fault based on its characteristics. According to [Yang, 2004], there are two categories of diagnostic methods considered: Knowledge-based (or Physical model based) Methods and Data-driven Methods.

2.2 Problem Statement

In process engineering, the importance of system monitoring for fault conditions has been widely defended, since the detection, the diagnosis and correction of system conditions, are components of AEM [Taylor and Sayda, 2005].

The major challenge in this context is to automate the process, since the AEM has been performed manually and increasingly complex processes have been analyzed. In the literature, many studies have been conducted to automate the processes of fault detection, according to [de Almeida et al., 2011], whose line of research predicts detection and isolating a fault (FDI - Fault Detection and Isolation).

According to [Yu et al., 2012], three steps are defined as follows.

1. Detection, in which occurrence of a fault is indicated after its occurrence;

2. Isolation, which defines the fault location;

3. Identification, in which the fault size and other features are estimated.

[1]Definition provided by the Cambridge dictionary

In this chapter, some related concepts are presented to the fault detection problem, focusing on the application environment and approaches based on Intelligent Systems for solving the problem. Some relevant information for fault detection in dynamic systems can be checked in [de Almeida et al., 2011, D'Angelo et al., 2011].

2.2.1 Redundancy in FDI

Redundancy models, as defined in [Frank, 1990], are based on the following methodologies:

1. Physical Redundancy - defined as replication elements required for performance measurement and process.

2. Analytical Redundancy - defined by calculating the residue corresponding to differences between measured values and the estimated / observed variables, defined by the models to be shown in section 3.4.

3. Abstraction - representation which corresponds to the adequacy of the data obtained in the process to algorithms. The goal of this representation is to adapt the models to algorithms that require a more abstract representation of the problem. This representation can be based on the two previous terminology, often being interpreted as some calculations on the measured data in the process.

According to [Chow and Willsky, 1984], which defines mechanisms for robust fault detection and whose work is based on analytical redundancy, there are two steps in the task of FDI systems:

1. Generation of residuals;

2. Decision making.

The first task is the use of models for fault detection and the second consists in analyzing the information represented by the residuals to detect and to even isolate a fault. The following section discusses these strategies in the analysis of dynamical system state of qualitative approaches, instead of using redundancy models, a symptom extraction can be performed using classifiers, as implied in [Liu, 2004]. According to [Mayorga and Sellier, 2006], adaptive observers can be employed for state and unknown values estimation at same time, when certain values are unknown and subject to changes.

2.2.2 Characterization of faults

In [Liu, 2004], faults are defined by their location, informed by their actuators, sensor or components, and according to variables, as additive or multiplicative. According to [Nayyeri, 2013,Carl et al., 2012], faults can be described according to their temporal characteristics, these concepts are relevant considering the nature of each fault.

1. Abrupt - Faults characterized by sudden and abrupt change of an observed value. Usually modeled by the step function.

2. Incipient - Faults characterized by gradual and progressive change of an observed value, different from abrupt faults, this type can be more difficult to detect, because it represents a more subtle signal variation. Can be modeled through the ramp function, whose slope indicates the speed at which the fault progresses. Depending on the process, is not a trivial type of fault is detected due to delay in detection issues.

3. Intermittent - Fault characterized by the repetition of abnormal variations in the observed values. Can be modeled by pulses at different instants.

In a study applied to power systems in [Joshua, 2012], two types of faults are considered (abrupt and incipient faults), since these are most common in case studies, as most of them consider the occurrence of a fault as an event.

Throughout this work, especially in Chapters 4 and 5, it can be seen that the modeling of these detectors is a difficult process due to the occurrence of noise considered in many existing dynamic systems in daily life.

2.3 Approaches

Many strategies have been adopted to provide detection with a high degree of reliability of operation of the systems. According to [D'Angelo et al., 2011], this demand resulted in the need for these systems supervision, which may be based on knowledge of the process or data using mathematical models or computational intelligence systems.

In a more general classification, strategies for fault detection can be based on quantitative models (residual or classification based models), and qualitative models (symptom or search based models).

2.3.1 Quantitative Models

Quantitative models employ analytical approaches for the signals generation measuring differences between measured and observed values of a dynamic system to measure the state of the system as its normality degree, as in [Wang et al., 2011b]. These approximations are generated by state observers, or also by neural networks trained with data to be in the Normal states, as in the flowchart in Figure 2.1.

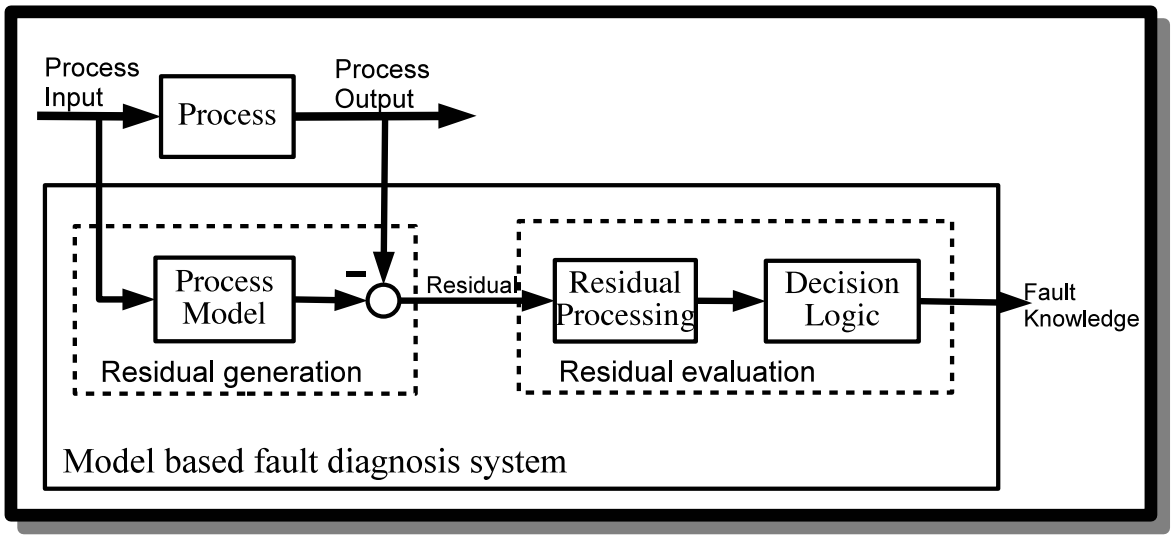


Fig. 2.1: Generic Model of a fault detection system, based on [Ding, 2008].

Residuals can also be used to isolate faults, and also can be used in same way as in pattern recognition, enabling the use of various tools. Some of these methods are described in [Venkatasubramanian et al., 2003a]. And the first stage of an FDI system is the fault detection, considered on most algorithms presented in this work.

2.3.2 Qualitative Models

Qualitative models are developed, according to [Venkatasubramanian et al., 2003b], based on some fundamental understanding of physical features of a dynamic system. These models are usually based on causal properties (cause and effect analysis) or on diagnostic search (based on topographies or symptoms) of possible abnormal states.

These systems may have some advantages over quantitative approaches, and the major disadvantage of them is the generation of spurious solutions and the need of a reasoning tool in order to generate the qualitative knowledge based on the modeling.

2.4 FDI as a classification problem

It is assumed that the main objective of a Fault Detection and Isolation system is the recognition of abnormal behavior (faults) of a process component, or process itself, through the monitoring of its variables and then recognizing adequately the fault patterns or the normal operation.

This idea of this approach can be understood from Figure 2.2. To enable a two-dimensional preview, consider a dynamic system which can be associated with this pattern to obtain this information on their operation. Consider coordinates $x_{p1}(t)$ and $x_{p2}(t)$ as inputs, outputs, estimated states, residue, or combination of these parameters. These coordinates define the space characterized as the ordered pair ($x_{p1}(t)$, $x_{p2}(t)$).

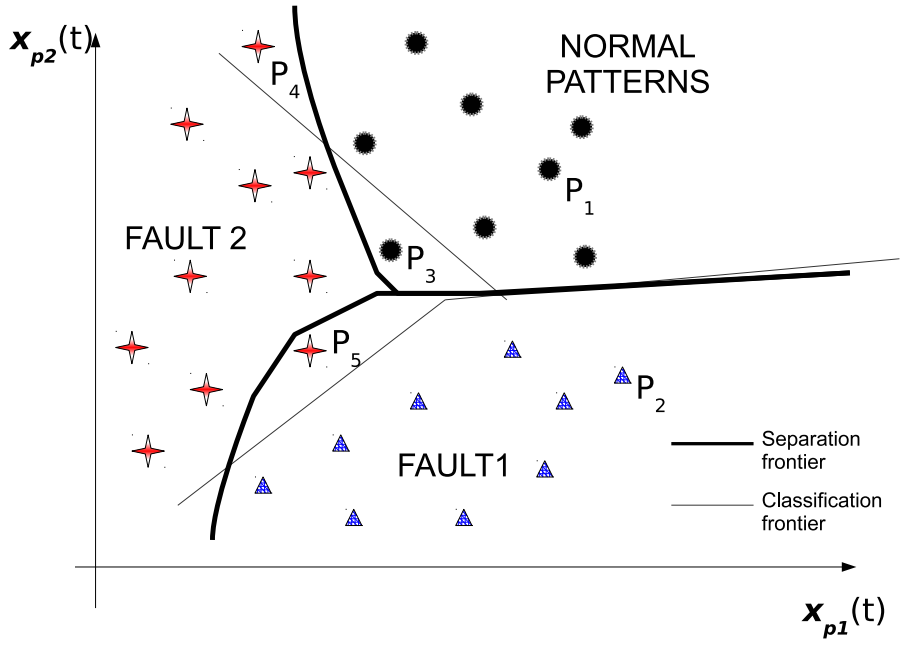


Fig. 2.2: Illustration of the Fault Classification Problem, based on [Caminhas, 1997].

For this system, consider three operating situations (classes): normal; Class-1 Fault and Class-2 Fault. These situations are separated by the border highlighted in Figure 2.2. Whereas the boundary is obtained by a pattern classification algorithm used to detect and isolate faults. Based on the boundaries of separation and classification may be illustrated indices for assessing the quality of a system fault detection, namely:

- False alarm (a normal operation classified as a fault class);
- Fault detected and properly isolated;

- Fault detected but incorrectly isolated;
- Failure to detect (a fault classified as a normal operation);
- and The fault detection time.

To graphically analyze these situations assume that the initial situation is normal system operation at t = t0, characterized by the pair ($x_{p1}(t0)$,$x_{p2}(t0)$) represented by the point P1. Consider the following situations:

- System operation at point P2, which belong to the region defined by the separation border, corresponding to a Class-1 fault operation. Based on the classification border, this point is also a Class-1 fault operation. Therefore, for the situation, the point P2 is detected and the fault is isolated correctly;
- The P3 point, based on the classification border, is classified as Class-2 fault operation, but corresponds to a normal condition, which is seen as a false alarm;
- The P5 point is labeled as Class-2 fault operation. As this point corresponds to a Class-1 fault operation, in which case the fault is detected, but isolated incorrectly;
- The point P4 represents a failure to detect the fault (Class-2 fault operation labeled as a normal point);
- The fault detection time: if a Class-1 fault occurs, represented by P2 point, the time spent to detect it is defined as the time in which the dynamic system has led P1 to reach Class-1 border.

It is observed that the more closer to the real separation border is the classification border, the better detection is provided by the FDI system.

Usually, the first stage of an FDI system is the fault detection, considered on most algorithms studied in this thesis. Fault isolation is performed if and only if an alarm is triggered by fault detection system. In addition, some fault types are not prior known, as considered in all case studies in this work.

2.5 Benchmarks

Some benchmarks were employed in the literature in order to provide validation on most FDI techniques. In this thesis, two benchmarks are employed and simulated to validate the algorithms proposed in this work.

2.5.1 The DC Motor Benchmark

The DC Motor benchmark was proposed in [Caminhas, 1997] in order to simulate the conditions of a Direct Current Motor in normal and anomalous states.

This benchmark can be described as a drive system which consists of two power supplies, controlled static converters, a direct current machine and a mechanical load. The system can be represented in shown in Figure 2.3. The block diagram of the entire system, including control, is shown in Figure 2.4. The speed controller, proportional integral gives the value of armature current reference. The control of the armature current is done by varying the supply voltage. This voltage is a function of trigger angle of the converter provided by current controller. The loop field, and provide the current control allows the drive system to operate above the rated speed at constant power, through field weakening.

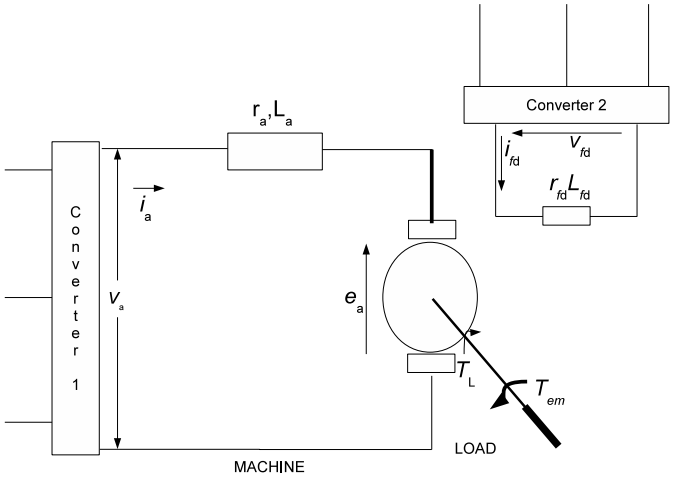


Fig. 2.3: Representation of the DC Motor system.

In Figure 2.3, we can describe each variable as the following:

- v_a represents the voltage of the armature circuit,
- v_{fd} represents the voltage of the field circuit,
- i_a represents the armature circuit current,
- i_{fd} represents the field circuit current.

and in Figure 2.4:

- ω_r represents mechanical rotation speed in rad/s,

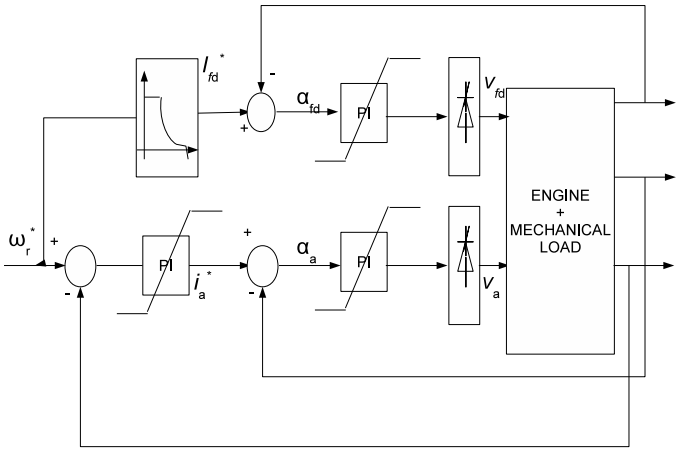


Fig. 2.4: Block diagram of the DC Motor system.

- α_{fd} represents the trigger angle of the field circuit converter,
- α_a represents the trigger angle of the armature circuit converter,

Those variables are indexed by n, which is related to the machine nominal values. The state variables are defined by:

- $x_1 = i_a$,
- $x_2 = i_{fd}$,
- $x_3 = \omega_r$

All state variables are measured, i.e. $y(t) = \mathbf{I}x(t)$.

In terms of fault analysis of the benchmark, three groups can be defined:

1. Actuators (armature and field converters);
2. Plant or process (in the DC Motor);
3. Sensors (current meters and speed).

Actuator faults usually occur in static converters. In the context of the DC Motor, this type of fault is characterized by short-circuit or disconnection of the machine components.

Plant faults can be represented by variations in resistance and inductance of the armature and field, faults in the ventilation system, that results in simultaneous variations of armature and field resistances, or poorly lubricated bearings, caused by variation in friction in the motor.

Sensor faults are characterized by shutdowns of current sensors (armature and field) and the velocity sensor.

Considering the three faults types discussed above, a summary of the fault modeling in the DC Motor benchmark is given in Table 2.1.

Tab. 2.1: Summary of DC Motor system faults.

Fault Index	Fault Type
1	Armature converter disconnection
2	Field converter disconnection
3	Armature converter short circuit
4	Field converter short circuit
5	Armature turns short-circuit
6	Field turns short-circuit
7	Ventilation system fault
8	Bearing lubrication fault
9	Armature current sensor fault
10	Field current sensor fault
11	Machine speed sensor fault

This benchmark has been previously used in [de Almeida et al., 2010] for tests with the multioperational version of NSA. In this work, the DC Motor is tested at Chapter 4, for tests with the fuzzy antigen recognition method, and at Chapter 5 for the validation of Dendritic Cell Algorithm metrics.

2.5.2 The DAMADICS Benchmark

This benchmark was proposed in [Bartys et al., 2006], for its purpose, three industrial actuators have been considered, with their structure being the same. The benchmark actuator belongs to the class of intelligent electro-pneumatic devices and is considered as an assembly of devices consisting of:

1. Control valve;
2. Spring-and-diaphragm pneumatic servomotor;
3. Positioner.

The actual conditions of the operation of a Polish sugar factory are simulated, in order to model actuators for industrial valves and to generate valid databases to validate detection methods and fault diagnosis features. The Figure 2.5 presents an illustration of the actuators.

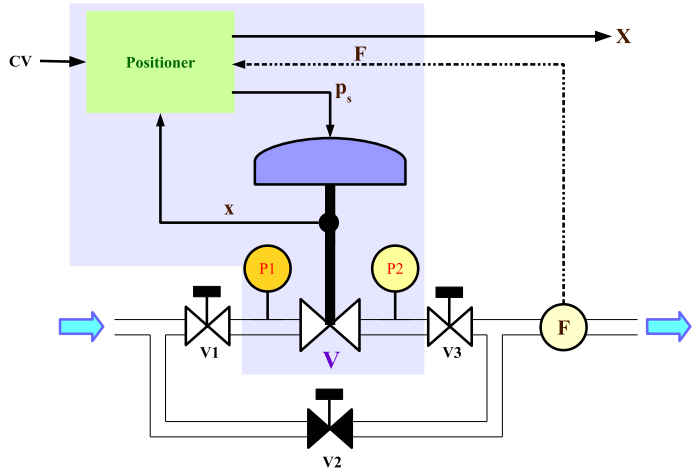


Fig. 2.5: The actuator of DAMADICS benchmark, based in [bmd, 2002].

Basically, according to [Kourd et al., 2013], this benchmark has the following mesurements: process control external signal CV, liquid pressures on the valve inlet P_1 and outlet P_2, liquid temperature T, liquid flow rate F and servomotor rod displacement X. Based on these inputs and outputs, the model is described in Figure 2.6.

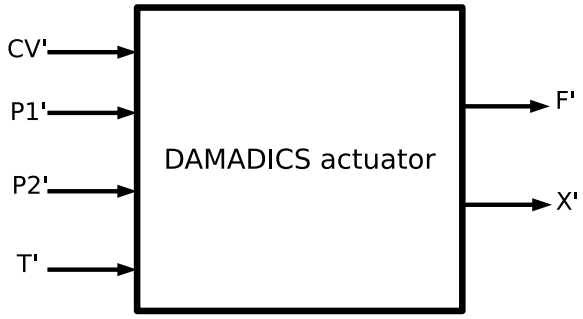


Fig. 2.6: Inputs and Outputs of DAMADICS.

DAMADICS faults can be simulated according to their intensity or nature (abrupt or incipient). There are 19 faults described for simulation in Table 2.2.

The DAMADICS benchmark was applied in several works in [Guzella et al., 2007,de Almeida et al., 2011,Lemos et al., 2013,D'Angelo et al., 2011], as well as in the earlier implementation of the Danger-based method, in [de Almeida et al., 2010], among others. Some previous researches have applied immune-inspired algorithms in DAMADICS using neural networks to generate

residuals for the decision phase, performed by AIS approaches.

In Chapter 5, some faults of the benchmark are tested with several immune-inspired techniques.

Tab. 2.2: Summary of DAMADICS benchmark faults.

Fault Index	Fault Location	Description
0	-	Normal Conditions
1	Control Valve	Valve clogging
2	Control Valve	Valve or valve seat sedimentation
3	Control Valve	Valve or valve seat erosion
4	Control Valve	Increase of valve friction
5	Control Valve	External leakage
6	Control Valve	Valve tightness
7	Control Valve	Medium evaporation or critical flow
8	Servomotor	Twisted servomotor stem
9	Servomotor	Servomotor housing or terminal tightness
10	Servomotor	Servomotor diaphragm perforation
11	Servomotor	Servomotor spring fault
12	Servomotor	Electro-pneumatic transducer fault
13	Positioner	Stem displacement sensor fault
14	Positioner	Pressure sensor fault
15	Positioner	Positioner spring fault
16	General or External	Positioner supply pressure drop
17	General or External	Unexpected pressure change across valve
18	General or External	Fully or partly opened bypass valves
19	General or External	Flow rate sensor fault

Chapter 3

State of the Art in Artificial Immune Systems

Artificial Immune Systems, alternatively known as Immune-inspired Systems or Immunological Computation, is a research line which is developed based on abstractions derived from the biological immune system. These abstractions are based on analogies that serve as metaphors for the development of methods and techniques inspired by the immune system in order to reproduce some features found in the biological immune system.

The AIS research field has been consolidated in [De Castro and Timmis, 2002], as an emerging computational intelligence method. Since then, some algorithms and methods have been developed in order to provide efficient solutions to many computational or engineering problems, such as anomaly detection, optimization, clustering, machine learning, among others as described in [Dasgupta and Niño, 2008, Dasgupta et al., 2011].The following section will bring some concepts and advances in these approaches.

3.1 Inspiration from nature to solve problems

Natural systems may be considered one of the richest sources of inspiration for the development of new systems, according to [De Castro, 2006, Afaq and Saini, 2011, Rozenberg et al., 2012]. Due to the complexity of most problems, obtaining reasonable solutions may be a demanding task and most conventional methods are unable to perform this task in a feasible time.

Many computational paradigms have been proposed, some of these inspired by natural phenomena to provide a system with same or similar features in order to solve complex problems, such as optimization, classification, clustering, machine learning, anomaly detection, among others.

These paradigms have been rearranged and categorized into a research field named Nature-Inspired Systems, a subdivision of Natural Computing research field which, according to [De Castro, 2006], consists of extracting ideas from nature to develop computational systems, or simulating and emulating natural phenomena, or even using natural resources to perform computation. And according to [Rozenberg et al., 2012], this field of study investigates models and computational techniques inspired by nature, as well as phenomena taking place in nature in terms of information processing.

3.1.1 A brief introduction to Natural Computing

Many computational systems or events have inspirations in natural or biological mechanisms. As defined by [De Castro, 2006], this principle, which provides several methods or solutions based on natural resources or inspirations, is the essential of the Natural Computing research field, which has three branches, namely:

1. Nature-Inspired Computing models - Solving of problems using nature as inspiration;

2. Simulation and Emulation of Natural Phenomena - Simulation of natural phenomena and mechanisms in computers;

3. Computing with Natural mechanisms - Using nature as source for hardware or information processing.

Data structures implementation that can complement or replace current computers developed in silicon may be studied in the third subdivision, **Computing with Natural mechanisms**. Such structures may constitute in DNA, RNA, quantum bits or membranes, allowing the development of "natural" computers.

The study of behaviors, patterns and natural or biological processes, as well as their simulations are discussed in the second subdivision, **Simulation and Emulation of Natural Phenomena**. In which Artificial Life models and some phenomena such as Fractal Geometry are considered.

Finally, the study of computational tools inspired by natural phenomena is the main proposal of the first subdivision, **Nature-Inspired Computing models**. In this group, strategies based on biological or natural mechanisms are proposed in order to provide the same features found in biological systems for solving complex problems. This subdivision includes the main focus of this research, as Artificial Immune Systems researches are methods inspired by natural and biological phenomena.

Some researches, as in [Kari and Rozenberg, 2008], may consider subdivisions 1 and 2 as a single subdivision in which nature serves as inspiration, including other researches, such as Cellular Automata and L-Systems, those applied both for problem solving and simulations; Membrane Computing, which has some applications as natural mechanism or to solve computational problems; and even Artificial Life simulations. However, in this particular case, simulating life or natural phenomena cannot be considered equal to use nature abstractions to solve problems, as the context and purpose of both subdivisions are different. Figure 3.1 shows a schematic representation of the connection between all main paradigms of Nature Computing, as well as their recurrent subjects in literature.

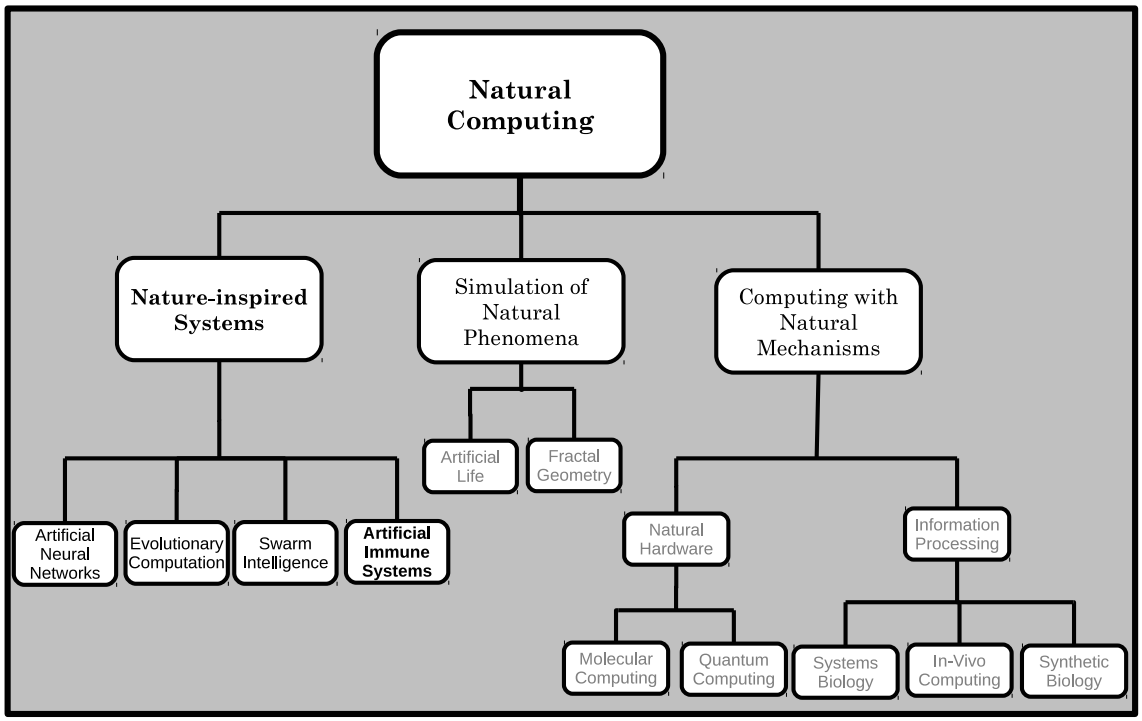


Fig. 3.1: The Natural Computing paradigms and their main research topics, with focus on Nature-Inspired Systems, based on [De Castro, 2006, Kari and Rozenberg, 2008].

As an emerging field the Natural Computing research has three major challenges according to [de Castro et al., 2011]: its consolidation as a transdisciplinary discipline, a more refined definition of information processing, and the definition of engineering of these systems. It is stated in the paper that this research field represents an environment of intellectual synergy that instigates the scientific community to reflect and rethink ideas and proposals in a transdisciplinary way. It is described in [De Castro, 2006] that Natural Computing yields novel and exciting capabilities for computer science, engineering, philosophy and the biosciences.

The Nature-Inspired Computing paradigm can be alternatively known as Bio-Inspired Computing, Computing with Biological Metaphors or even Biological Motivated Computing [De Castro, 2006], considering many of these inspirations related to biological phenomena. In addition, biology can have a broad meaning which incorporates not only biological, but also chemical and physical systems as well [De Castro, 2006]. This paradigm is widely applied to a large number of complex problems in literature, which will be further discussed.

3.1.2 Nature-Inspired Computing topics

The list of Nature-inspired systems includes, but is not limited to, the following types of computational intelligence approaches:

- Artificial Neural Networks
- Evolutionary Computation
- Swarm Intelligence-based Systems
- Artificial Immune Systems

All these systems have the biological inspiration as a feature, and may be applied to a wide number of problems. Computational intelligence systems have been heavily influenced by biological inspiration, especially in this context.

The biological influence is due to relevant features present in biological systems, such as memory, organization, learning, recognition, adaptation, robustness, tolerance and diversity in employment of these techniques. The expected result of using bio-inspired systems in their applications is to achieve better results in the solution of problems as the same features from biological system are provided by their computational counterpart.

For example, Artificial Neural Networks systems have an analogy with the brain and human connectionism. These systems are bio-inspired alternatives for machine learning systems. These systems can use supervised learning, as Perceptron or Radial Basis Functions, or unsupervised learning, as Kohonen's Self-organizing maps.

Evolutionary Computation systems are based on the evolution theory and use population based concepts. These algorithms rely on crossover operators, in which individuals from a given generation are able to produce new individuals, and mutation operators, in which an individual undergoes changes. These individuals are also influenced by selection mechanisms, which determines how satisfactory is the solution for a given application. Mostly applied for

optimization problems, some examples of systems from this paradigm are Genetic Algorithms, Differential Evolution, and Genetic Programming approaches.

Systems based on swarm intelligence, are also based on populations. However, unlike Evolutionary Computation systems, they are based on the influence of some individuals on the population according to the environment. In these systems, the behavior of one individual can influence the behavior of others and of the overall system according to predetermined rules. Systems based on Ant Colony follow this reasoning. Another system considered in this group is Particle Swarm Optimization, whose rules are based on the behavior of the best individual, either globally or locally.

Artificial Immune Systems are typically dependent on the application environment. For example, Anomaly Detection are determined by system functions according to the inspiration model adopted, which will be further discussed. For other applications, as in the case of Clonal Selection or Idiotypic Network based systems, this paradigm may have great similarities with Evolutionary Computation, however, within immunological contexts.

In addition to their application to Anomaly Detection problems, Artificial Immune Systems can also be applied to optimization, pattern recognition, clustering, machine learning, among other problems. As the biological immune system have many aspects to serve as inspirations, it is possible to apply AIS to these problems according to them [Dasgupta et al., 2003, De Castro and Timmis, 2002, Dasgupta and Niño, 2008, Dasgupta et al., 2011]. In Figure 3.2 AIS and their algorithms and abstractions are illustrated as a Nature-inspired system as well as the other paradigms.

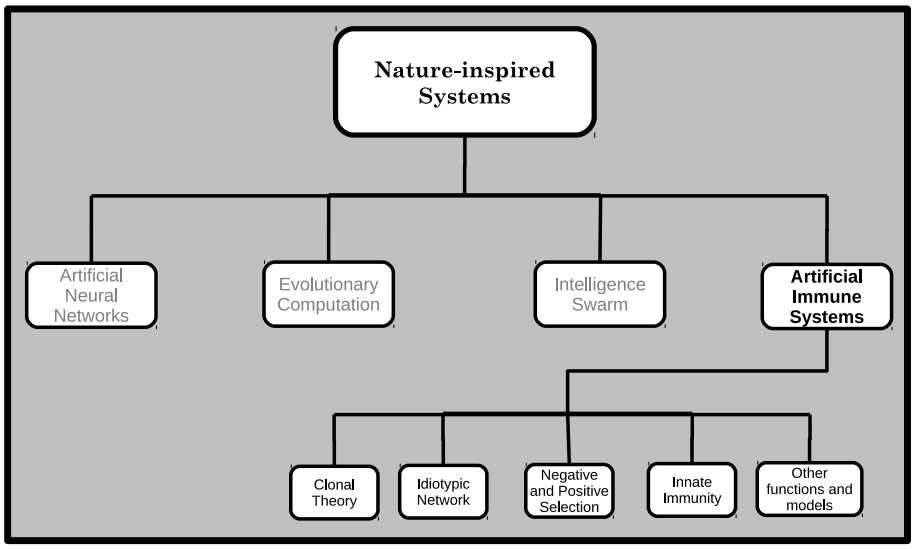


Fig. 3.2: Nature-inspired systems examples, with focus on Artificial Immune Systems. (adapted from [De Castro, 2006]

Newer AIS approaches are focused on innate immunity, possibly because of its relation to adaptive immunity in some immunological models, like the Infectious Nonself [Janeway Jr., 1989] and the Danger Model [Matzinger, 1994], considering the role of innate immunity in these models. Since Antigen Presenting Cells (APCs) such as dendritic cells and macrophages are represented as mediators for Th cells, some applications have exploited these features, one of them is the Dendritic Cell Algorithm (DCA), proposed in [Greensmith et al., 2005] and based on the Danger Model and APC functions.

Some other functions and models may include other functions or models that are not usually employed for analogies, such as the T-Cell Receptor Density [Owens et al., 2013], the Complement System [Aitken et al., 2008], Natural Killer Cells [de Almeida et al., 2011, Fu et al., 2012], Cross-Regulation mechanism [Abi-Haidar and Rocha, 2010], Tunable Activation Threshold [Antunes and Correia, 2009a] and the Cohen's Cognitive model [Andrews and Timmis, 2007], among others.

As AIS have many approaches which may be suitable for many sets of applications, they also can be compared to most Nature-inspired approaches as well. This comparison is also considered in [De Castro and Timmis, 2002] and may be extended as novel immune-inspired approaches have been introduced to literature.

3.1.3 AIS X Other Nature-inspired systems

In the Nature-inspired computing research field, Immune-inspired systems can be defined by their multiple aspects, incorporating some features from other approaches in different ways. These features in common with other nature-inspired systems will be further defined in a comparison between these approaches.

One of the advantages of Immune-inspired system is its applicability in various contexts and the possibility of multiple applications. Most nature-inspired paradigms would be applied to a particular set of applications, as further described in this comparison between AIS and them, based on some considerations of [De Castro and Timmis, 2002].

Artificial Immune Systems and Artificial Neural Networks

Artificial Neural Networks (ANN) are inspired by the human nervous system in the same way as AIS are inspired by human immune system as the neuron represents the information processing agents, interconnected by other neurons and forming the neural network, in order to provide learning features. Each neuron relies on weights, which defines the learning function and are adjusted during the training phase. Learning is the main feature found at these systems.

Tab. 3.1: Parallel between AIS and ANN

	Artificial Immune Systems (AIS)	Artificial Neural Networks (ANN)
Bioinspiration	Antigen recognition by immune cells (According to a given model or feature)	Connection among neurons
Representation	Shape-space, agents or mathematical modeling based.	Mathematical modeling based
Architecture	Population or network based	Network based
Adaption	Learning (NSA) or evolution (CSA/AIN)	Learning
Plasticity and Diversity	According to their components evaluation	Using constructive or pruning algorithms
Applications	Classification, anomaly/novelty detection, regression, clustering, optimization, among other problems.	Classification or regression problems.

ANNs are mainly represented by Multi-Layer Perceptrons, which may use a Feedforward architecture and the Backpropagation algorithm for a supervised learning; Radial Basis Functions, another supervised method; and Self-Organizing Maps, an unsupervised method which relies on a competition mechanism applied to neurons in the network. Recurrent Networks and Reinforcement Learning algorithms also represent this set of bio-inspired applications.

AIS, like ANN, can be applied to a large set of learning problems. Based on immune memory concepts, as memory cells are able to store information of a particular antigen in order to provide a faster and more effective response, learning is a feature implied by the immune memory in the adaptive immune system and can be provided by some immune-inspired approaches like Clonal Selection based algorithms.

The negative (and also positive) selection of lymphocytes, according to Self and Nonself Discrimination and assuming that a naive cell is presented to a given self antigen from body, is also a valid analogy which matches to the same supervised machine learning principles that are adopted by most neural network models. This feature will be further discussed throughout this work. At most, learning feature is the recurring similarity between both approaches. In Table 3.1, the differences between AIS and ANN are shown.

Artificial Immune Systems and Evolutionary Computation

Evolutionary Computation approaches are inspired by evolution theories, in which a population of individuals represents the set of potential solutions to a given problem and each individual

Tab. 3.2: Parallel between AIS and EC

	Artificial Immune Systems (AIS)	Evolutionary Computation (EC)
Bioinspiration	Antigen recognition by immune cells (According to a given model or feature)	Evolution of individuals based on chromosomes
Representation	Shape-space, agents or mathematical modeling based.	Stochastic modeling based
Architecture	Population or network based	Population based
Adaption	Learning (NSA) or evolution (CSA/AIN)	Evolution
Plasticity and Diversity	According to their components evaluation	Selection of most fitted chromosomes
Applications	Classification, anomaly/novelty detection, regression, clustering, optimization, among other problems.	Mostly for optimization problems.

has a genotypic (variables) and a phenotypic representation (fitness function). Best values for fitness solution represent potential best solutions for the problem. Through processes of reproduction, selection and genetic operations, population evolves in order to improve these solutions by generations.

Evolutionary Algorithms are mainly represented by Genetic Algorithms (GA), which relies on crossover and mutation operators as well as its selection operator applied to the population individuals, usually represented as binary chromosomes. Older algorithms as Evolutionary Programming (EP) and Evolution Strategies (ES) were also considered. Genetic Programming (GP), which is applied in a different context, as representation of computer programs, and Differential Evolution (DE), another evolutionary algorithm, also represent this paradigm.

Some AIS approaches applied to optimization problems have evolution based mechanisms. The main difference between these algorithms is regarding how the selection of best solutions may occur. In essence, clonal selection based algorithms have some resemblances with evolutionary approaches. In Table 3.2, the differences between both paradigms are shown.

Artificial Immune Systems and Swarm Intelligence-based Systems

Swarm Intelligence systems are a set of applications inspired in the dynamics of populations in a group, these approaches reproduce collective behaviors of a swarm, which can also represent good solutions for many applications, in particular, for optimization related problems.

This set of applications includes the Ant Colony Optimization System (ACO), inspired in the

Tab. 3.3: Parallel between AIS and Swarm Intelligence

	Artificial Immune Systems (AIS)	Swarm Intelligence based Systems (SIS)
Bioinspiration	Antigen recognition by immune cells (According to a given model or feature)	Collective behavior of many individuals
Representation	Shape-space, agents or mathematical modeling based.	Stochastic and mathematical modeling based
Architecture	Population or network based	Population based
Adaption	Learning (NSA) or evolution (CSA/AIN)	Collective behavior
Plasticity and Diversity	According to their components evaluation	Population changing according to collective behavior
Applications	Classification, anomaly/novelty detection, regression, clustering, optimization, among other problems.	Mostly for optimization or clustering problems.

ant communication through pheromones which represents pathways to find food; the Particle Swarm Optimization System (PSO), inspired in the collective behavior by most individuals imitate the best of their population or their own best experiences; and other algorithms such as Bee Colony [Bitam et al., 2010, Maia et al., 2012, Xu et al., 2013], Bacterial Foraging [Passino, 2002], Water Drops [Shah-Hosseini, 2009], Fish Swarms [Neshat et al., 2012], among others. The main idea of these algorithms is to exploit the main features of such inspirations as long as a given problem can be solved, once necessary.

These nature-inspired paradigm have been widely applied to optimization problems and then, comparisons to AIS approaches have been discussed in [Timmis et al., 2010], since both paradigms have many aspects of direct parallels, since Swarm Intelligence exploits the result of individual behaviors in coordinated population behavior as a whole and AIS exploits immune functions and models. Both approaches have been also discussed in terms of self-organization, positive and negative feedbacks, amplification factors and multiple signals of phenomena. The scientific and abstract aspects of swarm interactions have been discussed and both approaches can be considered as complementary fields of research that also can be combined to develop new techniques. In Table 3.3, the differences between both approaches are shown.

Similarities between AIS and SIS have been discussed in [Xiao et al., 2011], such as structure of individuals, their interaction, and system structures, as well as their learning, memory, feedback, and adaptability aspects, among other points. It is possible that Swarm Intelligence-based approaches, as well as AIS, are emerging approaches whose potential is still high for

analogy exploiting.

3.1.4 Important note about Nature-inspired Systems

Importantly, Nature-inspired systems do not necessarily have all the features of a particular biological system. For practical reasons, some implementation or specification of these systems may omit or even extrapolate some aspects. Moreover, Nature-inspired systems do not imitate biology like in Artificial Life based applications. Instead, nature serves as inspiration to develop computational systems in order to reproduce the same effect as a biological phenomenon to solve a problem.

3.2 Artificial Immune System Approaches

Artificial Immune Systems are developed based on abstractions derived from mechanisms present in the human immune system. According to the literature some of these mechanisms may provide key features such as distributed detection, imperfect detection, anomaly detection, adaptability, use of only positive samples, and uniqueness for solving problems, among others. These and the immune memory feature, are attractive for solving some engineering or computational problems.

Early works, starting from [Forrest et al., 1994], are focused on the Self/Nonself Discrimination principle applied to anomaly detection. These methods consist on supervised learning based techniques inspired on the negative selection process, which has a censoring feature occurred in the thymus.

As the biological immune system is a complex and distributed system with a large set of cells and molecules, and molecules serve as communicators, maintenance, transportation and signaling for cells, AIS-based solutions may rely on signaling based data applied to these systems, mainly for the novel approaches that requires a prior expert knowledge about the system behavior. Even some Self-Nonself based algorithms may require signal-based resources for a proper anomaly detection, as in [Guzella et al., 2007, Yu and Dasgupta, 2008].

The reason for inspiration in the biological immune system may be related to its robustness and the faster response provided in the human immune system, in which a more effective and faster response to an antigen is expected for its next occurrences, after the first time this same antigen was seen in the body. The expected objective of developing such approaches applied to a given problem is to reproduce expected behaviors from the biological inspiration in order to solve the problem effectively.

A first survey about AIS was done in [Dasgupta and Attoh-Okine, 1997]. A brief description about immune models, such as Immune Networks and Negative Selection, and applications of first immune-inspired approach, such as Computer Security, Pattern Recognition, Time Series Anomaly Detection and Fault Diagnosis, were reported in the survey, and then, in the first book about these systems in [Dasgupta, 1998].

The development of novel engineering tools based on immunological theories and models have been provided for many applications as seen on [de Castro, 2001], in which a framework for the development of immune-inspired engineering systems, as well as their applications, comparisons to other computational intelligence paradigms and also proposal for some hybrid systems were considered. Since then, applications such as Optimization approaches based on the Clonal Selection Theory or on the B cells, Pattern Recognition approaches and Clustering approaches based on the Immune Idiotypic Network.

Novel approaches to anomaly detection based on alternate models of the biological immune system, like the infectious nonself and danger models, have appeared. These models, implied by their biological counterpart, may depend on prior expert knowledge which defines normal and abnormal events, suggested by biological analogies, as the Self-Nonself principle, which relies on the Negative Selection process, analogous to a supervised machine learning method that defines the normal and anomalous feature space.

Most aspects of these algorithms, including alternate versions and improvements developed, are seen in [Dasgupta and Niño, 2008], a book in which many aspects and most immunological computation objectives and proposals are reviewed and discussed.

Algorithms that adopt multiple models for immunological abstraction (i.e. clonal selection algorithm applied to optimization of negative selection algorithms), the predominant model related to its research and applications focus will be considered in the list of methods in each subsection, since these methods can be combined and are not mutually exclusive.

3.2.1 Immune Response Models

An anomaly detection system evaluates data and verifies that these data follow normal patterns usually defined by prior knowledge achieved under training algorithms or some information provided by experts. As the accuracy of these systems relies on the specificity of normal data, some systems may present significant false alarm rates and misdetect some anomalies. For this reason, computational intelligence based systems has been widely employed, including Immune-inspired methods.

The main bottleneck of immunology was to define how the nature of the immune responses is in fact. The first accepted model in biology is the one based on clonal selection, whose

improvements are usually related to the concepts of Self-nonself Discrimination. However, as this principle has some controversial points, other immunological models have been proposed in order to explain some issues regarding some biological functions and immunity.

The Self-Nonself principle, which relies on the Negative Selection process, is analogous to a supervised machine learning method that defines the normal and anomalous feature space, as the Negative Selection Algorithms use Self-based training data for detectors generation through Nonself space.

As in biology, it was discovered that "nonself" antigens alone is not sufficient to trigger T cell activation, the model of costimulation signals would explain this issue, and then, other models of immune response were proposed to explain several immunological phenomena. These models have offered other analogies for AIS approaches, mainly related to anomaly detection systems, which would be applied to different problems, depending on the analogy.

Novel approaches to anomaly detection based on alternate models of the biological immune system. The danger model was stated at [Aickelin and Cayzer, 2002, Aickelin et al., 2003] as another way to develop novel AIS approaches, incorporating some aspects, such as, according to the authors: signals being indicators of behavior in the application rather than antigens; signals may indicate not only 'danger', but 'interesting' or 'relevant' information; and data analysis may require less human intervention than previous approaches, among other aspects.

Some of these aspects were considered in further approaches, as in [Greensmith, 2007, Greensmith and Aickelin, 2008, Twycross et al., 2010]. These alternate models, implied by their biological counterpart, may depend on prior expert knowledge, represented by signals, that defines how normal and abnormal events are detected.

All immune models, suggested by how response is triggered, according to their biological analogies, can be defined on Figure 3.3. Each approach has differences related to data analysis. However, all of them have a transitional link as described in [Costa Silva et al., 2012b]. With complementary functions to be further discussed, each immunological model has advantages and disadvantages that should be taken into account for each application environment.

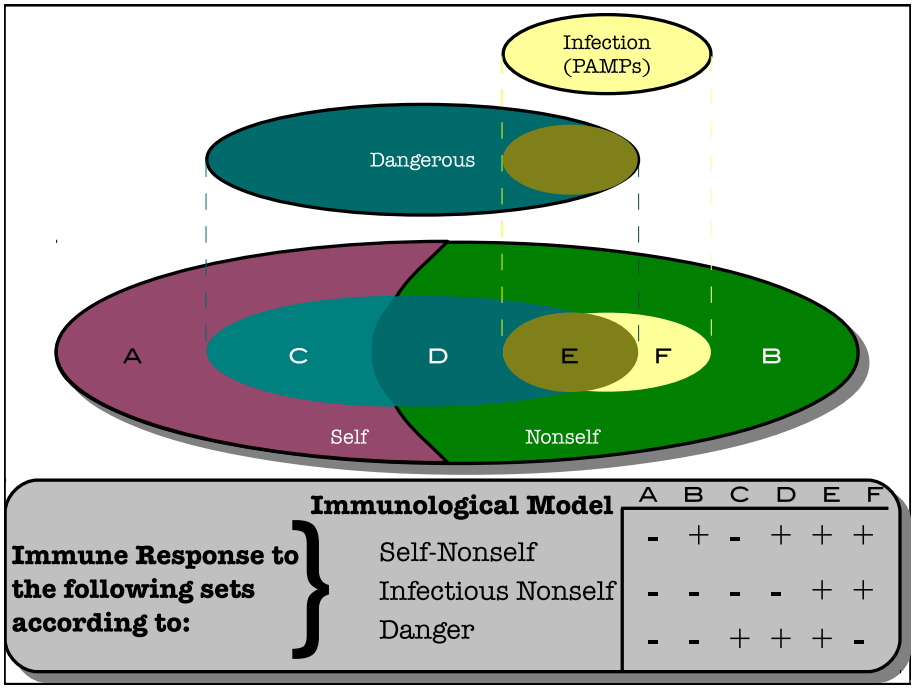


Fig. 3.3: All immunological models related to the immune response. [Matzinger, 2002] This illustration may provide analogies to anomaly detection applications.

Usually, Self-nonself and negative selection approaches are seen as a distinct group in AIS approaches, as well as immune networks and clonal selection approaches. In this survey, Self-nonself approaches and most models of immune response are grouped into algorithms based on the immune response, since these techniques are applied to anomaly detection and they have points in common, being a part of a transitional link.

The response models which inspire anomaly detection systems will be further discussed regarding the corresponding model, usually based on T cells or their interaction with antigen presenting cells (APCs), but not limited to this analogy. Since the immune system analogy is closely related to the anomaly detection problem, by providing a response to pathogens which may threaten the body, most algorithms are related to anomaly detection, but not all of them, as there are other aspects to be explored in these models. The following section will bring some concepts and advances in these approaches.

Self-Nonself/Negative Selection-based Algorithms

The concept of Self-nonself Discrimination defines the Biological Immune System with the purpose of defending the body against foreign substances (nonself). Considering these substances as potential causes of diseases, the body must respond to these. For this purpose, the immune cells, especially lymphocytes, should not recognize the substances in the body (Self) through a

maturation process, known as the negative selection. This process eliminates all lymphocytes which have high affinity to self antigens.

In Computer Networks Security, there are many problems related to system reliability and some Intrusion Detection Systems (IDS) are based on anomaly detection. In this case, according to [Catania and Garino, 2012] and [Chen et al., 2010], the normal traffic behavior is analyzed in order to generate a normal activity profile, and then, any deviation from this profile is considered an anomaly. The main advantage of these approaches is the high performance of unknown attacks recognition. However, these systems may provide some false positive or changes on user behavior problems. Some statistical or machine learning based methods, as well as some AIS approaches have been developed to provide more accurate systems. Initial works were performed in [Forrest et al., 1996] and an initial framework for NIDS was proposed in [Dasgupta, 1999].

In order to improve the training mechanism of NSA, several approaches were considered, as the *V-detector*, a well developed Negative Selection-based approach with coverage estimation. This algorithm was exposed to sensitivity tests in [Ji and Dasgupta, 2009] in order to expose its advantages and drawbacks.

Some other improvements for NSA were employed, as in [de Almeida et al., 2010] with some operators such as radius and detector overlap checking, in [Li et al., 2010] with an outlier robust inspired by immune suppression and applied for noise in [Wang et al., 2011a] with boundary management for detectors and in [Gong et al., 2012] with a further training mechanism. Detector generation aspects were reviewed in [Jinyin and Dongyong, 2011], and the cooperative co-evolution detector generation, a parallel gene-based model, is included. In [Wang et al., 2012], fractional distances are tested in order to verify their applicability to high dimensional problems, since data relative contrast is related to data dimensionality.

The traditional shape-space representations were evaluated in [McEwan and Hart, 2009], then, some classifiers and an alternative representational abstraction based in linear squares were presented to demonstrate the flaws of a n-dimensional based technique and how they can be outperformed by alternative representations. The basis discovery and decomposition in the immune repertoire representation were represented by a Matching Pursuit like process and based on equivalent algebraic and algorithmic mechanisms. The shape-space representation for machine learning AIS was considered inferior, because it is considered to reduce potential value of immune-inspired approaches.

The development of NS based approaches without detectors was considered in [Liśkiewicz and Textor, 2010], for string based applications. In this work, a fuzzy view of negative and positive selection processes was discussed with approaches proposed. In this view, antigen

recognition has a fuzzy nature and the objective of thymic selection is the maturation of cells with an intermediate affinity to self. This model considers both positive and negative selection mechanisms. Two approaches were proposed based on the model, one of them without detector generation but considering the nonself space as a deviation of self patterns according to a fuzzy inference system. The work in [Costa Silva et al., 2012a] introduces this method.

The main advantages of Negative Selection based algorithms are the ease implementation and intuitive principle, based on the input training data, the shape-space concepts, often based on r-contiguous or r-chunks for binary or strings data, and distance metrics like euclidean or hamming distance, depending on the data. The training phase of the algorithm also favors the approach by the management of the nonself Space. However, the algorithm has issues regarding the test phase, mainly because of its limitations due to the *curse of dimensionality* issue, as considered in [Balachandran et al., 2007]. In addition, these approaches may have some context issues that may represent a hindrance to a proper anomaly detection.

The Infectious Nonself/Pattern Recognition Receptors-based Algorithms

Some models were proposed in order to provide a proper explanation about biological immune system and its problems. One of them was the Infectious Nonself model, which extends the two-signal costimulatory model and tries to explain some elements that could lead to an immune response.

An approach considered in this group was the Conserved Self Pattern Recognition Algorithm, applied to a recurrent database of anomaly detection problems and improved with selective mechanisms and tests performed with comparative datasets among different approaches. The algorithm is also based on the Negative Selection, however, with costimulatory mechanisms based in the PRRs. An improved version of the algorithm applied to computer security was developed in [Yu and Dasgupta, 2011] with a near deterministic mechanism of detector allocation.

The Infectious Nonself model has also inspired a Dendritic Cell based approach: The Toll-like Receptor Algorithm was designed to intrusion detection problems with training mechanisms and a simplified signal scheme. The interaction between APCs and T cells is the basis of the algorithm. A Structured version of the algorithm was proposed in [Nejad et al., 2012], this version considers the Nonself space analysis a criterion for antigen recognition after signal exposure.

A NSA-based approach with PRR inspired mechanisms was proposed in [Zheng et al., 2013]. The named PRR-2NSA combines the inspiration on Pattern Recognition Receptors, whose data are generated via hard clustering and dissimilarity measurements, and a “Dual

Negative Selection" strategy, in which NSA is applied to classifier maturation to assure if it does not match with any other classifier, and once again to training data, to assure if it does not match with any normal data. The proposed algorithm is tested to dataset benchmarks and is compared to the 2NSA without PRR and the V-detector, with better performance. A similar strategy for APC data generation was adopted in the Semi-supervised Immune Classifier Generation Algorithm (SICGA) in [Ying, 2013], but with APC and PRR data being generated based on K-means algorithm and APC radius metric, and tests being performed in Iris, Chess and Breast Cancer Wisconsin datasets in comparison to V-detector results.

In summary, there are few approaches inspired on the Infectious Nonself model of immune response. However, this model is supposed to be a halfway between Self-Nonself-based Model and the Danger Model in terms of development of AIS approaches, as the concept of signals, implied by the pattern recognition receptors, and contextualization of anomaly represented by PAMPs or by a conserved self pattern are features that indicate anomalies in an application.

Danger Model-based Algorithms

Another proposal was the Danger Model, usually referred as Danger Theory[1], which defines that the immune response occurs during a distress event from the body, and activation signals are sent by damaged cells. Both models also define a higher influence of innate immunity on adaptive immunity.

Introduced in [Aickelin and Cayzer, 2002] as a new immune-inspired paradigm and designed for computer security applications in [Aickelin et al., 2003], this immunological model would provide a second generation of immune-inspired algorithms. Mainly represented by the Dendritic Cell Algorithm, proposed in [Greensmith et al., 2005, Greensmith, 2007, Greensmith and Aickelin, 2008] and evaluated in [Greensmith and Aickelin, 2009], these algorithms were based in the correlation between system behavior (Danger and Safe signals) and potential anomalous processes (Antigens).

The algorithm was further simplified in order to work as a deterministic algorithm, with further formalization, formulations, advances, comparison to other algorithms, functionality analysis and complexity analysis, which clarifies most implementing issues for the algorithm. Mathematical aspects related to its geometrical interpretation and linearity are also discussed. A progress analysis and some suggestions about all these DCA mechanisms were discussed in [Ding et al., 2013], and an updated study is seen in [Gu et al., 2013].

Besides DCA, there are more approaches inspired on this immunological model, such as an

[1]The Danger Model is seen as a theory, but according to immunologists, it is postulated as a model rather than a theory. This is also applied to Infectious Nonself Model.

optimization method (DMIA), seen in [Xu et al., 2012]; another fault detection method, seen in [de Almeida et al., 2010], a classification method in [Zhang and Yi, 2010], among others.

The Danger Model inspiration can provide many interpretations about the problem environment, mainly in anomaly detection problems, for which this paradigm is widely employed. The expert knowledge is one of the main forms of representation for the analogy, which does not necessarily need to represent danger contexts. Unlike most models representation, Danger Model based approaches may not need a training phase for its algorithms, but a proper representation of its signals is necessary, as stated in [Costa Silva et al., 2012b], and how to obtain this representation for some problems is still a recurring challenge in literature. Some tests in malware detection in [Shafiq et al., 2008] indicate that DCA detection is good, as it has a low rate of false alarms, but compared to other approaches, is far from perfect, even the real-valued negative selection has a higher detection rate according to some results.

Even in some intrusion detection problems, the Danger Model has some limitations such as antigen sampling, robust signal selection and time correlation problems, and some adaptations may be provided for the analogy, as discussed in [Vella et al., 2010]. Depending on the context, these algorithms may need an expert model to be employed and provide proper results.

3.2.2 Clonal Selection and Idiotypic Network approaches

The Clonal Selection Theory[2] is related to the expansion of lymphocytes, antibody formation in response to the antigen presence, and faster responses in further new exposures to the same antigen. This theory has inspired the Clonal Algorithm (CLONALG) [de Castro and Von Zuben, 2002] applied to optimization and machine learning problems, as well as classification problems, as in [Sharma and Sharma, 2011]. The algorithm has somatic hypermutation, with some insights reported in [Jansen and Zarges, 2011] and their importance to an application context in [Ulutas and Kulturel-Konak, 2013], diversity features and is able to search for local and global optima solutions. Since then, it has been widely applied to many optimization problems in the literature. A deep and comparative survey of some approaches, with the emerging research about these algorithms are discussed in [Al-Sheshtawi et al., 2010, Ulutas and Kulturel-Konak, 2011].

Some possibilities of improvements are being considered, such as in [McEwan and Hart, 2010], the Competitive Exclusion mechanism of clonal selection was discussed, based on generation and filtering aspects, the mathematical models involved and some biological aspects discussed. And in [Oliveira et al., 2013] which adopts an alternative representation for the algorithm inspired by the Pittsburgh-style representation in Genetic-Based Machine Learn-

[2]The Clonal Selection, according to immunologists, is in fact accepted as a theory.

ing, selecting as few instances as possible to represent the training set data without accuracy losses and number of required instances is set dynamically and evaluated during the affinity assessment.

Some other interesting algorithms were also developed, such as multiobjective versions of the algorithm evaluated in [Yunfang, 2012], a Genetic Programming based approaches in [Jabeen and Baig, 2010, Gan et al., 2009] or a combination with the Gene Expression Programming (GEP) in [Karakasis and Stafylopatis, 2008, Tang et al., 2010], implementation of Immunoglobulin-based mechanisms in [Chung and Liao, 2013], some improvements in AIRS algorithm in [Jenhani and Elouedi, 2012, Golzari et al., 2011], the application to reinforcement learning in [Karakose, 2013, Riff et al., 2013], associative rules for classification in [Mohamed Elsayed et al., 2012] and as a motif tracker for time series in [Wilson et al., 2010], among other approaches.

Clonal selection theory has contributed in several aspects for the development of different systems, many of them applied to optimization related problems. Immunological memory and cloning have been explored, and some operations such as somatic hypermutation, affinity maturation and the selection itself, have been exploited in order to solve more complex optimization, or even machine learning problems. Since the proposal of Clonal Selection-based algorithms, these approaches have been widely studied and some improvements were proposed.

The Artificial Immune Network paradigm is inspired on the Idiotypic Network Hypothesis [Jerne, 1973], in which is postulated that immune responses may be triggered through idiotypes, possibly unique to antibody and supposely expressed on Immunoglobins (B-cells), also discovered on TCRs. These idiotypes are able not only to recognize antigens, but they can recognize paratopes from other receptors, allowing mutual interactions between immune cells and providing more effective responses. The network theory has inspired some approaches, such as an immune network for diagnosis in [Ishida, 1990], a learning model in [Hunt and Cooke, 1996] and a data mining application in [Knight and Timmis, 2001, Timmis et al., 2000], among other models. These approaches may share many features with Clonal Selection-based approaches and employs more sophisticated features.

The aiNET approaches, which shares some functions with clonal selection algorithms, are studied in [de França et al., 2010, Zhang et al., 2013, Xu et al., 2010, Liu et al., 2010], for different applications. Some example of Immune Network approaches can be applied to data mining applications as a decentralized algorithm in [Święcicki, 2008] or the autopoietic model based in [Nanas et al., 2010], or clustering applications as the Adaptive Immune Response Network in [Liu et al., 2009] or a hierarchical clustering approach in [Chen and Zang, 2011], or resource allocation in [Li and He, 2013, Yang et al., 2011], and multi-agent systems as in [Hilaire

et al., 2010], among other applications.

Some interesting applications of immune network theory are in automated systems, such as in [Khan and de Silva, 2012], in which the immune network is applied to a self regulated fault tolerant multi-robot cooperation system, as a robot is modeled an antibody and its interaction environment is modeled as antigen. The objective of the application is to provide coordination and cooperation among robots. Other robotic-based applications of immune-inspired systems can be seen in [Raza and Fernandez, 2012].

Some earlier immune network approaches have been developed as an extension for the clonal selection based methods. However, since the analogy has been more explored throughout last years, some novel and interesting approaches have also appeared in literature in order to provide solution of other problems, such as robotics and data mining. Clustering and optimization are still a recurrent application of the immune network based approaches as well. These aspects will be further discussed in the research analysis.

3.2.3 Algorithms based on other models

The further approaches presented here are based on other models or features of the immune system and these approaches are focused on other analogies provided by the immune system. Some of them can serve as alternative approaches to different applications.

A novel AIS approach based on the density of T cell receptors is proposed in [Owens et al., 2009] and further explained in [Owens et al., 2013], the algorithm is based on a mathematical model of TCR density and feedback estimation, with a comparative to some kernel density estimation based techniques. The algorithm was applied to 2-type anomaly detection tests, to a chemical agent monitor detection in [Hilder et al., 2012], and in a system of fraud detection in [Huang et al., 2011].

The Artificial Immune system with DENsity sensitiveness (AIDEN), proposed in [Pathak et al., 2012], is a clustering method that also adopted a density concept. The method considers the stimulation of the TCRs and their interaction to B cells in the form of Antigen Recognition Balls. Some tests were performed in artificial data, with qualitative evaluation of clusters found.

The complement system, which has three pathways for its activation, was explored in [Aitken et al., 2008], as the algorithm developed is inspired on its alternative pathway, based also on the message passing process among software agents and requires a matching function. The authors, however, have discussed the model aplicability to engineering problems, which is still unknown.

In [de Almeida et al., 2011], a novel AIS appied to fault detection was developed. The novel approach is inspired on Natural Killer cells functions, which employs receptor balance

and the education process, features of NK cells in their lifetime. The algorithm was tested in DAMADICS benchmark and evaluated, with interesting results compared to other approaches.

Natural Killer Cells have inspired another algorithm in [Fu et al., 2012], in which are exploited the analogy of activating and inhibitory signals to monitor a computational system for spyware detection. The induction of cytokines by NK cells corresponds to each action performed by the system through web, indicating the presence of spyware. Experiments have shown some promising results and the applicability of NK analogies to the problem.

A constraint optimization algorithm based on T cells was developed in [Aragón et al., 2008], in which T cell are divided in three groups and the model is adapted througt the dynamic tolerance factor, which changes according to a new population and is calculated according to violated constraints and their relation to each cell type population. Three mutation operators are proposed according to cell types. Benchmark problems were tested and compared to stochastic ranking algorithm. An improved version of the algorithm was proposed in [Aragón et al., 2010] to handle constrained optimization problems and in [Aragón et al., 2011] for dynamic optimization problems.

The Dynamic Effector Regulatory Algorithm (DERA) was proposed in [Guzella et al., 2007]. This method incorporates cytokines and regulatory cells in the algorithm and adopts a different concept of Self and Nonself spaces, which relies on the distribution of effector and regulatory cells that recognize normal and abnormal processes. The algorithm was applied to the fault detection DAMADICS benchmark, with a considerable performance over other approaches.

In [Twycross and Aickelin, 2010] it is shown how innate immunity can be modeled in terms of multi-level data fusion mechanisms and how real-world problems should reflect an environment which can be seen as a combination of innate and adaptive immune systems as well. These models should provide a framework for realtime computer intrusion detection and further AIS approaches.

The Humoral Artificial Immune System (HAIS) in [Narayanan and Ahmad, 2012] applies diverse concepts for supervised learning and relies on similarity measures, affinity thresholds, maturation and hypermutation, among other mechanisms. The algorithm is applied to some benchmark datasets, with its parameters explained and memory cells feature evaluated in comparison to ANN training. The HAIS has a comparable performance as the obtained by AIRS algorithm.

In [Suarez-Tangil et al., 2011] the immune system learning and memory features are explored to study how to turn the generation of event correlation rules an automatic and efficient features and detect novel multi-step attacks by applying AIS to optimize Security information event managements.

The work in [Figueredo et al., 2011] proposes some comparison regarding two types of simulation: Simulation of Dynamic System (SDS), a mathematics-based immune model, and Simulation Based in Agents (ABS), in which effector cells of the immune system and their behavior facing tumor cells are modeled. For these two models, two AIS approaches were derived.

The T-cell Cross-Regulation model has inspired an application in [Abi-Haidar and Rocha, 2011, Abi-Haidar and Rocha, 2010], which consists in an agent-based method inspired by the dynamics of a population of T-cells and APCs for a single antigen recognition. The model is applied to data classification and feature selection, particularly in Biomedical Article Classification problem, for which the proposed method is tested and validated, the authors, however, state that the model needs to be improved with more sophisticated features.

Another AIS approach was developed in [Antunes and Correia, 2009a, Antunes and Correia, 2010, Antunes et al., 2009], the algorithm is based in the tunable activation threshold (TAT), which is a key mechanism for homeostasis, a dynamic equilibrium which represents one of two immunological concepts adopted in the algorithm, the other is cells clonal size regulation. The algorithm (TAT-AIS) employs this model for T cells and is able to recognize unknown patterns in temporal anomaly detection problems. The TAT hypothesis based algorithm has also applied to intrusion detection in [Antunes and Correia, 2009b, Antunes and Correia, 2011].

The cognitive paradigm of immune system [Cohen, 2000], which states that immune system recognizes both self and nonself and immune responses are mediated through cooperation of immune cells, has inspired an information retrieval architecture in [Hu et al., 2008]. The proposed system relies on interactive networks between agents of the system and a co-evolutionary mechanism led by an affinity maturation through the networks. Studies about development of systems inspired on this paradigm have started in [Andrews and Timmis, 2007, Voigt et al., 2007], but since then, few works have explored this paradigm of immune system, which can provide interesting analogies.

According to [Hart et al., 2009], modeling collaborative network among immune entities can lead to the development of novel approaches fit for their purpose of solving engineering problems. Analogies are taken from innate immunity and their interaction to the adaptive immunity elements, modern models of immune networks, and the cognitive paradigm. These analogies were discussed and then related to some real-world applications.

3.3 A brief summary about Hybrid AIS approaches

AIS can also be combined to other approaches as described in [De Castro and Timmis, 2002], with description of diverse combinations of paradigms, and in [Dasgupta and Niño, 2008], with the example of Negative Selection and Self Organized Maps model described. The development of hybrid systems has increased in the literature, not only for AIS, but for many other nature-inspired algorithms. This survey will further describe the influence of hybrid approaches in AIS research.

Hybrid system can be divided in two groups. In the first group, it will be discussed the use of tools or methods that can extend or enhance AIS to provide proper features in problem solving, such as Probability Theory, Fuzzy Logic, Information-based Tools, among others. In the other group, systems that employ different algorithms or techniques with their functions mixed will be discussed, such as Artificial Neural Networks, Evolutionary Algorithms, Swarm Intelligence Algorithms, other machine learning methods, among others.

3.3.1 Useful tools for AIS enhancement

Several tools can be employed in order to extend AIS features or to enhance most aspects, such as probability or tools based on the Bayesian theory, fuzzy set theory, information theory, kernel methods, among others since they are not considered as specific algorithms. Hybrid approaches involving multiple algorithms will be further discussed in the other group.

Some of these tools have been already adopted in early approaches, as in the example of the first Self-Nonself based system in [Forrest et al., 1994], whose detection is probabilistic. Several methods rely on these tools for modeling purposes, according to features that should be provided for a particular problem. In addition, algorithms based on clonal selection need these features because of their stochastic nature as these are applied to generation of antibodies and in the somatic hypermutation operators. However, since these features were not the focuses of their respective approaches, but features incorporated to these systems, they cannot be considered as hybrid approaches at all. As each tool can enhance AIS functionalities, a further discussion will be presented of some of these tools.

In this group, some tools can be used to provide enhancement for AIS, in terms of functions and mechanisms. The following list includes, but is not limited to these considered approaches:

- Probabilistic methods, such as Gaussian or Bayesian;
- Fuzzy and Rough sets theory;
- Information theory tools;

- Kernel Functions;
- Other learning and memory mechanisms;
- Chaos theory, quantum computing and other methods.

These tools can be used to improve or replace mechanisms on AIS approaches, in the case of probabilistic methods. Examples of these techniques are the family of Probabilistic Artificial immune Systems based on Negative Selection in [Mohammadi et al., 2012] and both Bayesian Artificial Immune System (BAIS) [Castro and Von Zuben, 2008] and Gaussian Artificial Immune System (GAIS) [Castro and Von Zuben, 2010] applied to optimization, with these algorithms also having multiobjective versions.

Fuzzy Set Theory, which can deal with uncertain or imprecise information, may offer proper models of aspects and mechanisms of the immune systems, providing powerful interactions, according to [De Castro and Timmis, 2002]. These aspects are considered mainly for adaptive immunity features, as the antigen recognition is approximate. However, the use of Fuzzy Logic is not limited to these aspects, as the immune system has several components. Some examples of algorithms are an Immune Network based in [Szabo et al., 2012], a Dendritic Cell-based in [Chelly et al., 2012], and the fuzzy recognition algorithms proposed in [Costa Silva et al., 2012a].

Information theory tools have been used to enhance AIS functions through entropic divergence metrics, such as Kullback-Leibler, Rényi and von Neumann, or the Dempster-belief Theory, which performs classification by computing evidences. One example of these approaches are the Local Concentration (LC), proposed in [Zhu and Tan, 2011b], to perform feature extraction and is based on tendency calculation via probability of occurrences, the vector of local concentrations is constructed by sliding window measurements of both censored and legitimate genes. The LC model can be constructed based on term selection that can be employed by information-based methods.

The use of kernel functions was less considered, and the discussion in [Guzella et al., 2008] has presented how kernel functions should extend AIS functions and features in the same way as used in machine learning paradigms such as SVM algorithms. The possibility of replacement of affinity functions by kernel functions were considered to map feature space. A test using aiNet approach mapped in a Gaussian space was performed in the research. In [Ozsen et al., 2009], a kernel-based AIS for classification inspired on clonal selection was proposed, and the affinity function between Ag-Ab is replaced by a kernel-based distance measurement. Benchmarks of UCI Database were applied to the proposed method.

These are some examples of useful tools in the development of different techniques or the improvement of existing ones without altering significantly the main idea of either the abstract model of an algorithm or functions for which these algorithms were designed for. Instead, these tools should provide a better suitability of the model or even permit the feasibility of an analogy for the development of new techniques applied to problem solving. Approaches that are developed mixing multiple techniques or employing features of different algorithms or even paradigms will be further discussed in the next subsection.

3.3.2 Hybridization of AIS and other paradigms

In this subsection, hybrid approaches that use mechanisms from AIS and other algorithms or even multiple algorithms will be discussed. Differently from the other group, in which paradigms or tools are implemented in terms of AIS modeling, in this group, all approaches employ different algorithms in the same system, in a high level of system hybridization. The list of approaches that can be used for this purpose include, but are not limited to the following:

- Nature Inspired approaches:
  - Artificial Neural Networks;
  - Genetic Algorithms and other evolutionary algorithms;
  - Swarm intelligence approaches;
- other Machine Learning systems:
  - Naive Bayes;
  - K-Nearest Neighbors (KNN);
  - Support Vector Machines (SVM);
  - most Clustering algorithms.
- Fuzzy systems:
  - Fuzzy C-means;
  - Takagi-Sugeno systems;
- Meta-heuristics;
- Meta-learning tools;

Examples of applications for possible hybrid AIS are mining rules from neural networks, weight optimization, ensemble in classification problems and generation of rule bases, among others.

Other examples of these approaches are combinations of AIS and PSO, as PSO may be applied to antibody improvements under mutation operators in classifiers or clustering methods. Several approaches were discussed in [Wu, 2012], including a novel immune-inspired method, presented to solve constrained global optimization problems.

There are many possibilities of hybrid approaches, since there are many paradigms to be considered. How these algorithms can be applied to a given problem is also another aspect of these mixed systems, since these algorithms, as well as AIS approaches, can serve as ensemble for one or many algorithms, or improve features or results of a given algorithm, or even be a part of the algorithm processing. The approaches cited here are some examples of how AIS can improve or be improved by other techniques to solve harder problems, as for their complexity, a single algorithm may not be enough.

Some of these combinations, however, may imply redundant features, since AIS have features in common with other paradigms of machine learning or mainly nature-inspired applications, which are subject to similarities between paradigms, as in the example of Clonal Selection algorithms and Evolutionary Algorithms approaches. Some other examples will be further discussed in the sense of AIS research.

3.4 Immune Response Algorithms

According to [Beutler, 2004], a "true" immune system, independent of its complexity, must provide three features: the recognition of diverse array of pathogens, their posterior elimination, and protection of host tissues through self-tolerance. If these concepts provide an analogous vision of an immune response based anomaly detection, the features considered in these systems should be described as follows:

1. An AIS is able to recognize diverse types of anomalies;
2. Once recognized, an alarm signal is sent, or proper actions are performed;
3. Performs detection without interference on other operations, or in the normal operation as well.

Early works have been inspired by self-nonself discrimination principle, such as the computer virus detection approach of Forrest in [Forrest et al., 1994], and many approaches and improvements were done since then.

The models studied in this work follow the description of [Greensmith and Aickelin, 2009], describing the evolution of immunological theories, along with the corresponding immune inspired approaches. These models are based on signal presences required for immune response, as defined in Figure 3.4.

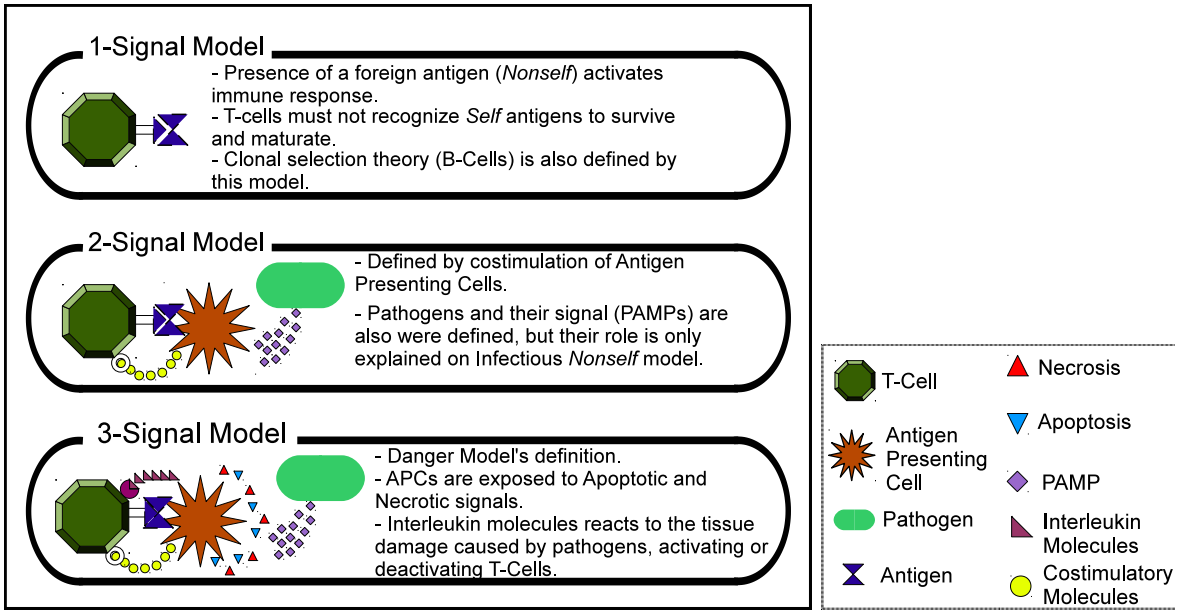


Fig. 3.4: Description of immunological models discussed.

In the following subsections, some immunological models and their respective algorithms will be discussed. Their characteristics and applicable situations, as well as the advantages and disadvantages of these algorithms will be exposed in the research.

3.4.1 The Classical Model

The model is based on the Self-Nonself Discrimination principle, in which immature cells which recognize Self patterns are eliminated by the Negative Selection process. The first immune inspired algorithms were developed from this principle.

The Negative Selection Algorithm (NSA), defined in [Forrest et al., 1994], is an anomaly detection system that consists of analyzing the feature space, and through it, generating detectors in the Nonself region. The algorithm has resemblance to supervised machine learning methods, since the Self data is used as a reference, so that the detectors are located outside of Self region.

The method in fact, can be summarized as the one-class supervised classification problem, in which only one of the patterns (Self) is known and the outliers may belong to another class (Nonself), as shown in Figure 3.5.

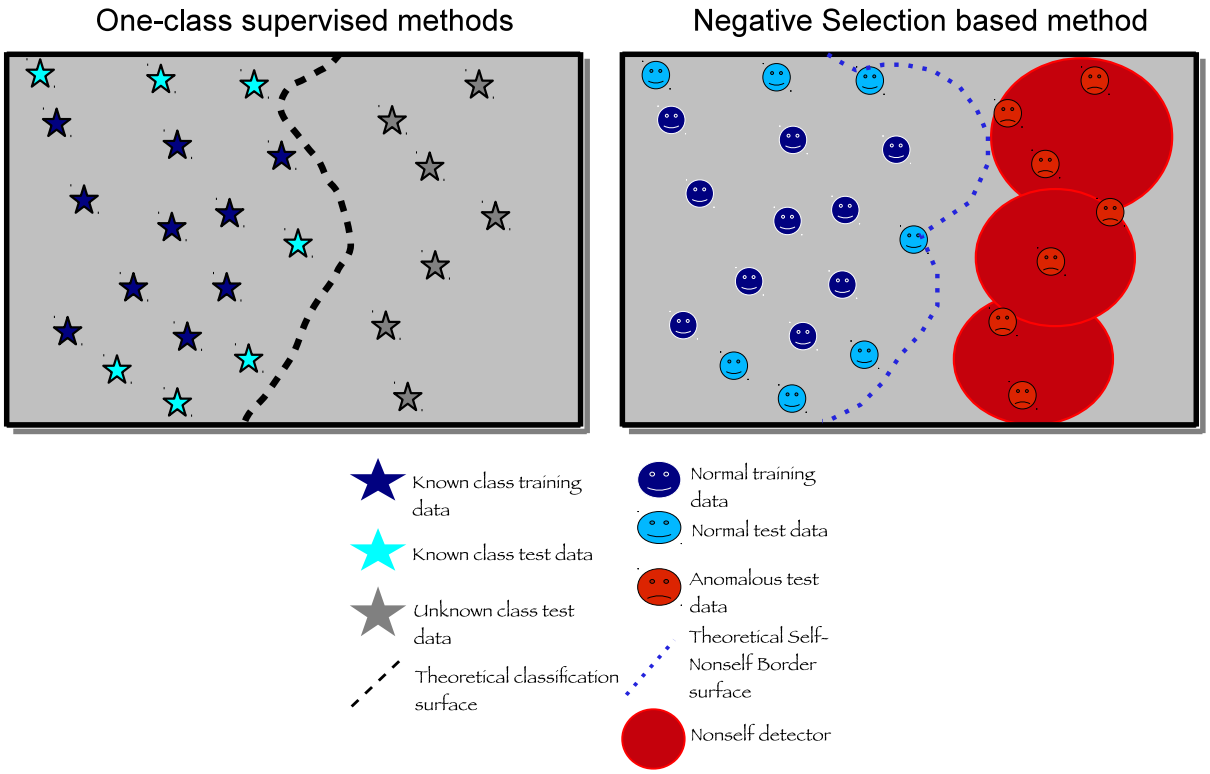


Fig. 3.5: Illustration of similarities between one-class supervised classification and anomaly detection based on *Self/Nonself* principles.

Many approaches appeared trying to improve operational aspects such as optimization of the coverage area to detectors [Ji and Dasgupta, 2004b], allocation considering boundaries of Self space [Ji, 2005], or overlap on two or more detectors [de Almeida et al., 2010]. In [Gong et al., 2012], it is considered a training method that optimizes the computational cost of the algorithm. Other improvements are considered in [Ji and Dasgupta, 2007].

The algorithm is very intuitive and quite simple but has many issues: to allocate the detectors and measure the similarity between these and the data may imply something quite costly and redundant, especially in high-dimensional problems. Furthermore, the algorithm has serious problems concerning the system context. Other issues can be seen in the analysis of [Ji and Dasgupta, 2006].

Despite the issues, the NSA is applicable to problems where there are few abstractions on the application and it is possible to set normal behavior. However, the algorithm is very limited considering the application environment.

3.4.2 Costimulatory and Infectious Nonself Models

The costimulatory model defines that two signals are required for the activation of the immune response: the nonself antigen presence and a signal emitted by Antigen-Presenting Cells. This model has inspired few researches in computer networks, such as [Hofmeyr, 1999, Balthrop, 2005]. These models can be considered intermediate or transitional between the Negative Selection and the Danger Model.

The model was proposed in [Janeway Jr., 1989] in attempting to explain some phenomena that, in theory, Self-nonself discrimination could not deal with. In this model, T cells rely on pattern recognition receptors (PRR) which recognize infectious pathogens and collect Pathogen Associated Molecular Patterns (PAMP) for the activation of immune response.

This model represents a "half-way" between the classical immunology, and the next model combining known data sampling and some priori information about the application context.

The Infectious Nonself has provided few AIS models in the literature so far. One of these techniques is the Toll-Like Receptors algorithm. Proposed in [Twycross et al., 2010] with ideas presented in [Aickelin and Cayzer, 2002], the TLR is inspired by an immune model defined in [Kapsenberg, 2003], and employs functions analogous to Toll-like receptors in information processing tasks, as explained in Figure 3.6.

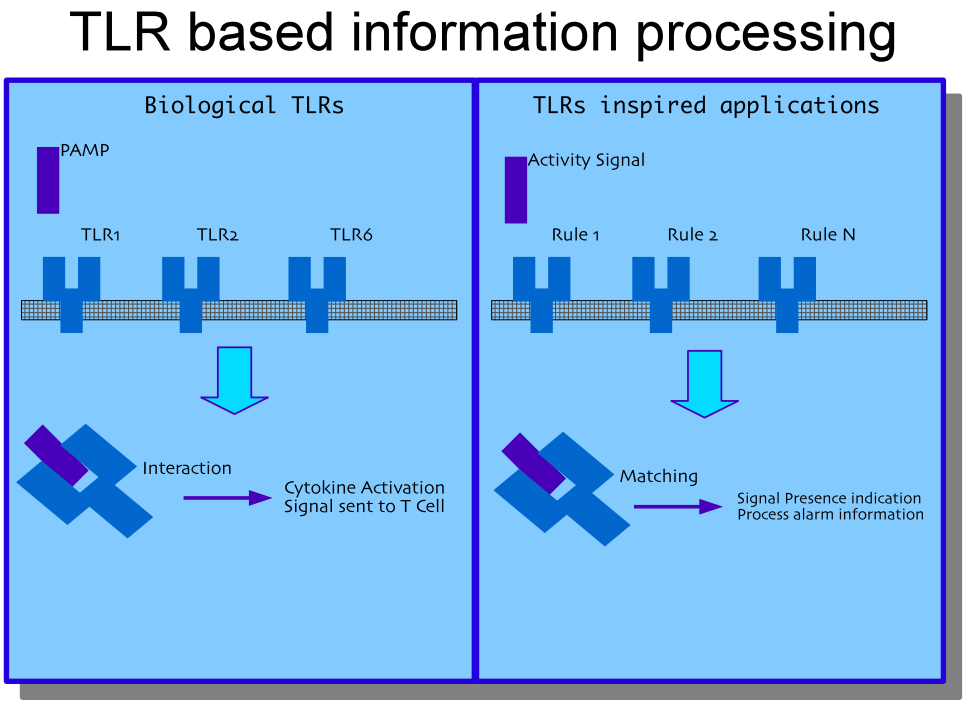


Fig. 3.6: Biological processing of Toll-Like Receptors and its analogy with data processing systems.

This algorithm consists of a technique based on the interaction between two agents: APCs and T cells that are exposed to stimulus analogous to PAMPs and collect the antigens represented by process identifiers. These agents and their possible states are illustrated in Figure 3.7.

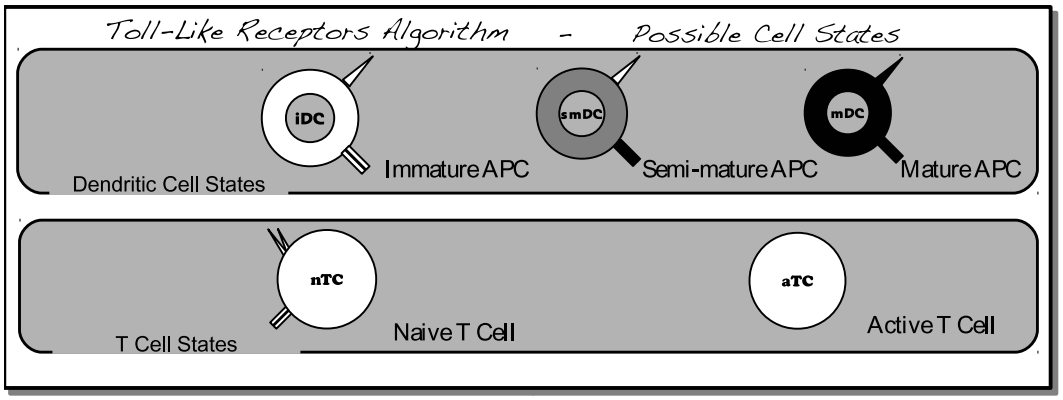


Fig. 3.7: Agents used by the algorithms of Toll-Like Receptors and their possible states.

Signals are defined by Boolean variables and once the APCs are exposed to these signals, they suffer full maturation. This is essential for antigen recognition by T cells in communication with mature APCs. When APCs cannot see this signal, during their lifetime, these cells goes semimature, and if a semimature APC presents an antigen to the T-cell, the latter undergoes apoptosis. This mechanism can be summarized by Figure 3.8.

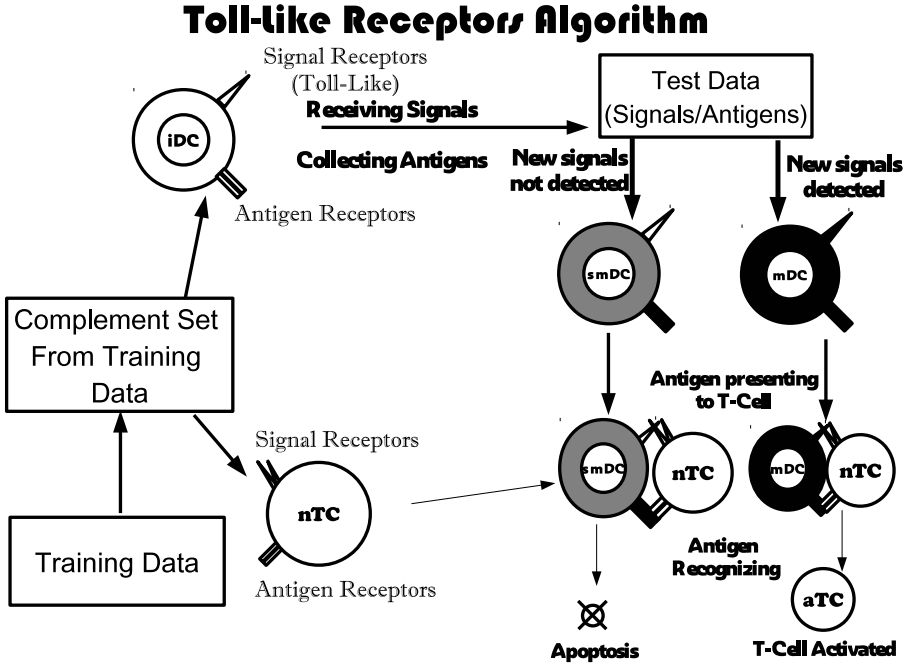


Fig. 3.8: Summary of the Toll-Like Receptor algorithm.

Despite the ease of abstraction, implementation requires the definition of mechanisms of training, a proper definition of signals and most features of the algorithm for the two types of considered cells.

In [Nejad et al., 2012], the Structural TLR (STLR) algorithm was proposed. The algorithm provide some changes in which T cells were related to the self and nonself spaces with the detection mechanism provided by antigen-presenting cells. Once exposed to the signals and defined as mature cells. This algorithm associates T cells to nonself space modeling, defined as the complement of the self space. Then, the nonself space is defined by antigen structure as recognition is given by the binding function between the antigen and a sample self space, according to (3.1).

$$\zeta_{Ag} = \begin{cases} 1, & \forall i \in Tr,\ Dist(Tr_i, Ag) > r_s \\ 0, & \texttt{otherwise} \end{cases} \tag{3.1}$$

$$\tag{3.2}$$

Where Ag is the antigen (data structure) and $Dist(a, b)$ is a distance metric between a and b, and is usually defined by the Euclidean distance or the Mahalanobis distance. In summary, the STLR has features of algorithms based on Negative Selection, however, most mechanisms are described in the original TLR in [Twycross et al., 2010].

Main functions of Toll-like Receptor Algorithm can be summarized in the flowchart of Figure 3.9 and in Algorithm 3.1.

STLR was applied to intrusion detection problems with interesting results and a relative superiority to the original TLR. As this algorithm has been only applied to intrusion detection problems, some changes should be considered for its application FDI problems. Some ways to process the algorithm will be described in the following sections, considering its modeling.

3.4.3 The Danger Model

The Danger model[3], postulated by [Matzinger, 1994], is an alternative to classical immunology defending another point of view related to the immune system: immune response aims to respond to the damage suffered by cells instead of reacting against foreign antigens.

This immunological model would inspire a set of new AIS approaches [Aickelin and Cayzer, 2002, Aickelin et al., 2003] in which the application context can be exploited, once the set of

[3]In the literature, this model is often called "Danger Model". However, considering its nature, the best name should be "Damage Model".

Algorithm 3.1 Pseudocode of TLR Algorithm

procedure TRAININGTLRALGORITHM(Ag_{Tr},$Signal_{Tr}$)
  $Self \leftarrow$ BUILDNONSELFSPACE(Ag_{Tr}) ▷ Build Nonself Space with a detection algorithm.
  $SignalRules \leftarrow$ BUILDSIGNALRULES($Signal_{Tr}$) ▷ Build rule database from training.
return $Self$,$SignalRules$
end procedure

procedure TESTTLRALGORITHM(Ag_{Ts},$Signal_{Ts}$,$Self$,$SignalRules$,$NumCells$)
  $Cell \leftarrow$ GENERATECELLS($NumCells$) ▷ Generate cells to evaluate data.
  $c \leftarrow 1$
  $k \leftarrow 1$
  while not($StopCriteria$) **do**
    $Cell_{(c)}.Ag \leftarrow$ GETANTIGEN(Ag_{Ts}, k) ▷ Cell collects antigen.
    $Unseen \leftarrow$ UNSEENSIGNAL($Cell_{(c)}, Signal_{Ts}, k, SignalRules$) ▷ Cell receptor senses signals.
    if $Unseen = true$ **then**
      $Cell_{(c)}.Status \leftarrow Mature$
      $Migrated \Leftarrow c$
    else
      if $Cell_{(c)}.Lifetime \leq 0$ **then**
        $Cell_{(c)}.Status \leftarrow Semimature$
      else
        $Cell_{(c)}.Lifetime \leftarrow Cell_{(c)}.Lifetime - 1$
        $Migrated \Leftarrow c$
      end if
    end if
    for all $m \in Migrated$ **do**
      $Match \leftarrow EvaluateNonselfSpace(Cell_{(m)}, Self)$
      if $Cell_{(m)}.Status = Mature$ **then** ▷ APC is mature.
        if $Match = true$ **then** ▷ Antigen is Nonself.
          $Alarm \leftarrow true$
        else ▷ Antigen is Self.
          $Alarm \leftarrow false$
        end if
      else ▷ APC is semimature.
        $Alarm \leftarrow false$
      end if
      $Cell_{(m)} \leftarrow$ RENEWCELL($Cell_{(m)}$) ▷ Replace migrated cells.
    end for
    $Migrated \Leftarrow \emptyset$
    $c \leftarrow \mathbf{mod}(c, NumCells)$
    $k \leftarrow k + 1$
  end while
return $Alarm$
end procedure

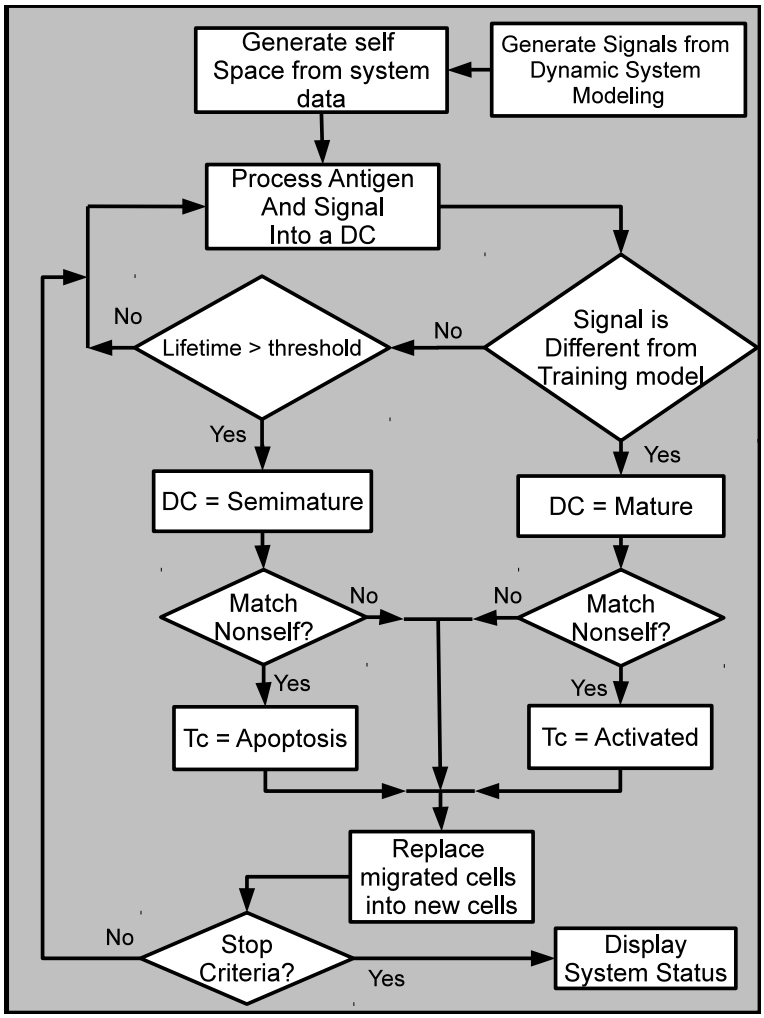


Fig. 3.9: Flowchart of the Toll-Like Receptor Algorithm.

signals and analogies are well defined in this model.

Dendritic Cell Algorithm, proposed in [Greensmith et al., 2005], has these characteristics. Antigen in this approach are identifiers to be evaluated and the signals set corresponds to the system behavior. The original algorithm formulation determines four possible types of input signals, two stimuli signals (Danger and PAMPs), an inhibition signal (Safe) and an amplifier that depends on the other three signals; and three output signals, one of which corresponding to the lifespan of the cell and the other two corresponding to the context of dendritic cells, indicating that the immune response.

Unlike the TLR algorithm, DCA does not represent the T cell by an agent of the algorithm. Their representation is inferred by a decision mechanism that evaluates the antigen according to the maturation of dendritic cells that have collected. Such signals consider the conditions of the application environment in the problem, without training on the system.

Em [Greensmith, 2007], the algorithm would be applied to problems related to intrusion detection in computer networks, among they SYN scan, and is promising for the application in the problem. Then the algorithm was applied to similar applications in [Al-Hammadi et al., 2008, Manzoor et al., 2009, Fu et al., 2010], and engineering [Bi et al., 2010, Amaral, 2011, Hart and Davoudani, 2009].

These signals correspond to representations of expert knowledge about a particular problem and for the application of DCA to a specific problem, by the context of an application.

In [Greensmith and Aickelin, 2008], Danger and Safe signals are required and the other two signals are optional. The input signals are processed to generate the CSM values in(3.3), which determines the lifespan of the cell, and K values in (3.4), which combines two maturation signals. These equations define the basic formulation of anomaly detection problems in DCA.

$$CSM = DS + SS \tag{3.3}$$

$$K = 2DS - SS \tag{3.4}$$

Usually, safe signals is stronger than danger signals, so the equation defines a high weight to the latter in K.

When the variable CSM reaches a threshold for cell migration, a maturation process occurs. If K is positive, cell becomes mature, which means the activation the immune response, and if K is negative, cell becomes semimature, which means suppression.

After maturation of dendritic cells, antigens collected by such cells should be placed according to mature cells obtained considering the type and maturity suffered by these cells. One way to classify the antigen using the DCA is under an index of cells collected by a certain antigen ($MCAV$) calculated in (3.5). This index has been proposed in the classical DCA [Greensmith, 2007], and if an antigen reaches a $MCAV$ value larger than a certain threshold, the antigen is flagged as anomalous.

$$MCAV(a) = \frac{M(a)}{M(a) + Sm(a)} \tag{3.5}$$

Another metric considered is the K_α, proposed in [Greensmith and Aickelin, 2008]. Unlike the $MCAV$, the K_α considers the magnitude of K related to all cells which collected the antigen a, as in (3.6).

$$K_\alpha(a) = \frac{\sum K(a)}{\sum DC(a)} \tag{3.6}$$

Basically, the illustration of Figure 3.10 summarizes the main functions of the algorithm.

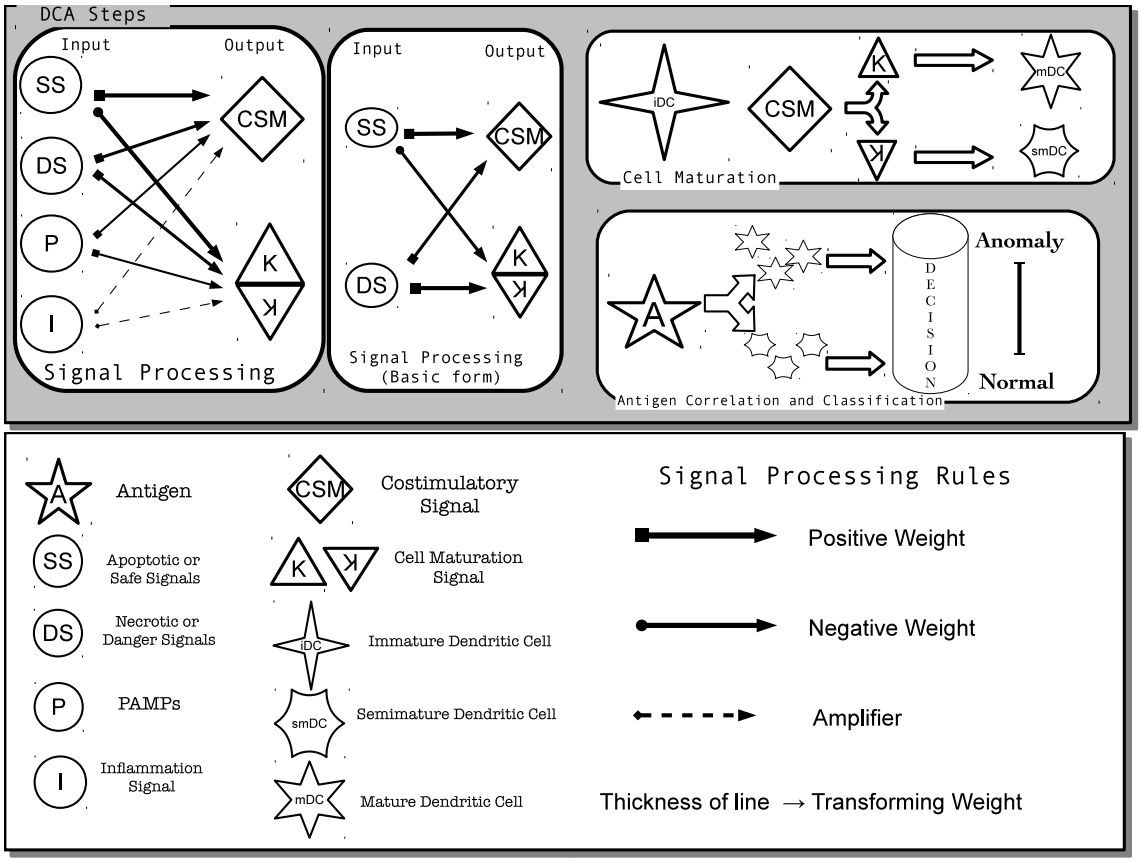


Fig. 3.10: Fundamental steps of the DCA.

The Dendritic Cell Algorithm main idea can be summarized in the flowchart of Figure 3.11 and in Algorithm 3.2.

Analogies and knowledge representation implied by the algorithm makes it an interesting alternative to problems of anomaly detection, with some potential applications. However, the prior knowledge of these problems are very important, especially in FDI applications.

In [de Almeida et al., 2010] another algorithm based on the danger model was developed especially for the problem of fault detection. Unlike DCA, the algorithm does not use cells agents, neither depend on interpretation of antigen data, but defines signals as a basis for its operation and provides a fuzzy inference model as an input and an immune mathematical model as an output, and alarms according to model metrics.

Other approaches that also exploit aspects contained in the Danger model consist in [Zhu and Tan, 2011a] regarding a model applied to different classifiers, and in [Zhang et al., 2008] which applies concepts to define an interest region of an algorithm applied to optimization problems.

Algorithm 3.2 Pseudocode of DCA

```
1: procedure DendriticCellAlgorithm(Data,NumCells,NumRecep,MaxLifetime)
2:     DataSet ← PreProcessing(Data)  ▷ Perform Pre-processing and normalization in system knowledge data.
3:     Cell ← GenerateCells(NumCells, NumRecep, MaxLifetime)  ▷ Generate cells to evaluate data.
4:     c ← 1
5:     k ← 1
6:     while not(StopCriteria) do
7:         if DataSet_(k).Type = Antigen then  ▷ Data evaluated are antigens.
8:             Ag ← DataSet_(k).Content
9:             Cell_(c).Antigens ⇐ Ag
10:            if AntigenExists(AntigensList, Ag) then
11:                AntigensList ⇐ Ag
12:            end if
13:            c ← mod(c, NumCells)
14:        else if DataSet_(k).Type = Signal then  ▷ Data evaluated are signals.
15:            for all dc ∈ Cell do
16:                SignalSet ← DataSet_(k).Content
17:                Cell_(dc).Lifetime ← Cell_(dc).Lifetime − CalculateCSM(SignalSet)
18:                Cell_(dc).Output ← Cell_(dc).Output + CalculateK(SignalSet)
19:                if Cell_(dc).Lifetime ≤ 0 then
20:                    if NumberOfAntigens(Cell_(dc)) > 0 then
21:                        Migrated ⇐ dc
22:                    end if
23:                end if
24:            end for
25:        end if
26:        for all m ∈ Migrated do
27:            for all a ∈ Cell_(m).Antigens do
28:                idx ← AntigenIndex(AntigensList, Cell_(m).Antigens_(a))
29:                if Cell_(m).Output > 0 then  ▷ DC is mature.
30:                    M_(idx) ← M_(idx) + 1
31:                else  ▷ DC is semimature.
32:                    Sm_(idx) ← Sm_(idx) + 1
33:                end if
34:                K_(idx) ← K_(idx) + Cell_(m).Output
35:                {Alarm, AntigenStatus_(idx)} ← AnomalyMetric(M_(idx), Sm_(idx), K_(idx))
36:            end for
37:            Cell_(m) ← RenewCell(Cell_(m))  ▷ Replace migrated cells.
38:        end for
39:        Migrated ⇐ ∅
40:        k ← k + 1
41:    end while
42: return Alarm, AntigensList, AntigenStatus
43: end procedure
```

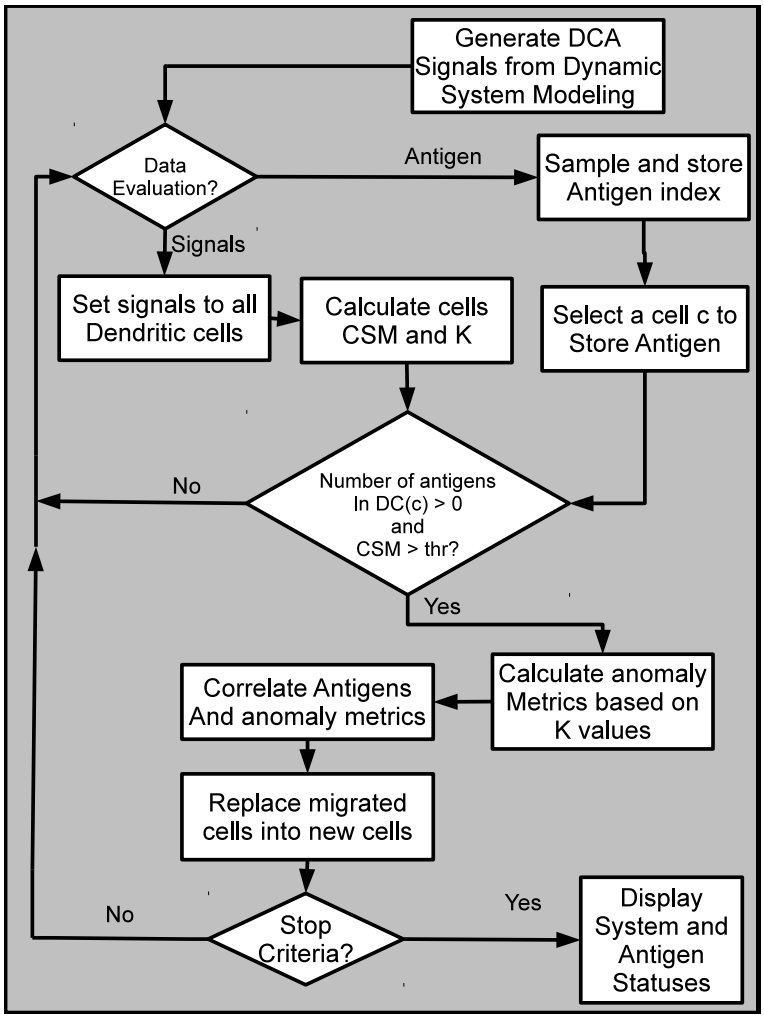


Fig. 3.11: Flowchart of the Dendritic Cell Algorithm.

3.5 Impacts in biological research

Immunology serving as a source of inspiration for computational systems may provide some multidisciplinary links and many interactions among researchers from different fields of study and a perspective of benefits for immunology, computer science and engineering respective researches, as further discussed in terms of AIS impact in biology and how computation could inspire biological models in research.

Reviews done in [Timmis et al., 2008] point that the development of AIS algorithms may provide interdisciplinary links between immunology, computer science, mathematics and engineering, since the immunology provides metaphors for the creation of novel solutions to problems. The authors have provided a framework for modeling novel approaches from immunology through a methodology evaluation, some reference models and the further development of

techniques from the abstract model, as well as some features to be provided in newer AIS approaches. It is also suggested that these models may help immunologists in bringing some understanding of the immune system as well as proper representations in AIS for engineering systems through greater interaction between each group of researchers.

As immunology may inspire computer systems, computation can also be an inspiration for insights about immunology, as defined by Cohen [Cohen, 2007], in this work are described the view of the immune system as a computational entity and immunological concepts and functions in terms of computation. Some computation concepts were applied to immunological components, such as the system states, its cells and their actions in the immune system. The paper also reinforces the need of interactions between immunologists and computer scientists.

The research in [Navlakha and Bar-Joseph, 2011] was related to biological modeling and inspiration for strategies to problem solving as well as the similarities between computation and biology and their differences. According to the authors, computational systems are often focused on speed and biological systems are focused in dynamic adaptability to changes and their decision-making mechanisms. This suggests that biological inspirations are very useful to computational systems. Features of biological and analogous computational systems are discussed and their research was considered as a *computational thinking of biological systems*, which provides more understanding of biological processes as well as improvements in algorithms development.

The ecology of immune system is discussed in [Tauber, 2008], in this paper, the author also discuss the 'Immunocomputing' research described as immunology formalization aspects and its quality as a fruitful source for applications to various problems. It is also implied that AIS is involved in multidisciplinary studies including fields of immunology modeling, mathematical modeling and computer simulations, among other forms of simulating immune models.

The artificial immune systems research, as seen on these works, may provide some significant contributions to immunology in the sense of understanding the immune system, as well as providing a multidisciplinary research between immunologists and computer scientists or engineers in order to establish interactions that should improve the understanding of the real functions of immune systems and reinforce the development of novel techniques and provide better results in problem solving.

At the present moment, there are few works pointing this aspect of AIS. However, there are some definitions stated in [Hart et al., 2009], such as 'Immunoengineering', which is inspired on immunoecology (study of principles applied to immunological functions) and immunoinformatics (related to decision making paradigms), whose elements are reunited to provide adaption and applications. Thus, the concept of an 'Immunoengineering' has been started in [de Castro,

2001], with the purpose of AIS approaches for problem solving.

These studies would provide a framework that supports the development of mathematical and computational models, as well as their validation through benchmark problems. In summary, understanding AIS may reinforces the understanding of immunological principles and models, as well as provide the growth of the research on bio-inspired systems.

Algorithms that adopt multiple models for immunological abstraction (i.e. clonal selection algorithm applied to optimization of negative selection algorithm), the predominant model related to its research and applications focus will be considered in the list of methods in each subsection, since these methods can be combined and are not mutually exclusive.

Chapter 4

Fault Detection and Diagnosis using Fuzzy Model of Antigen Recognition and Participatory Clustering

A model which presents the immune response as a process of fuzzy nature is defined in [Leng and Bentwich, 2002]. The model considers the T and B cells selection in the body through on fuzzy recognition of molecules as follows: i) in the case of low affinity, cell suffers death by neglect and ii) when affinity is high, cell dies in the negative selection process. This model defines that the immune response objective would be the generation of sub-optimal clones.

This model is illustrated in Figure 4.1 and can provide inspiration for anomaly detection systems, mainly for negative selection based algorithms, which can be described by these rules. The inference system considered in this work is described in [Chen and Mahfouf, 2009], in which the fuzzy output is used for the immune response of the fault detection system.

4.1 Fuzzy Antigen Recognition Algorithms

4.1.1 Detectors generator algorithm

The presented model complements some previous algorithms used for negative selection based detector generation, with the fuzzy inference mechanism to control detectors generated in a proper way.

The algorithm uses some system normal operation sampling as reference (training) data and system with fuzzy recognition of antigens to manage the allocation of detectors in nonself region. The rules are described in Table 4.1, and these rules provide fuzzy inference system in

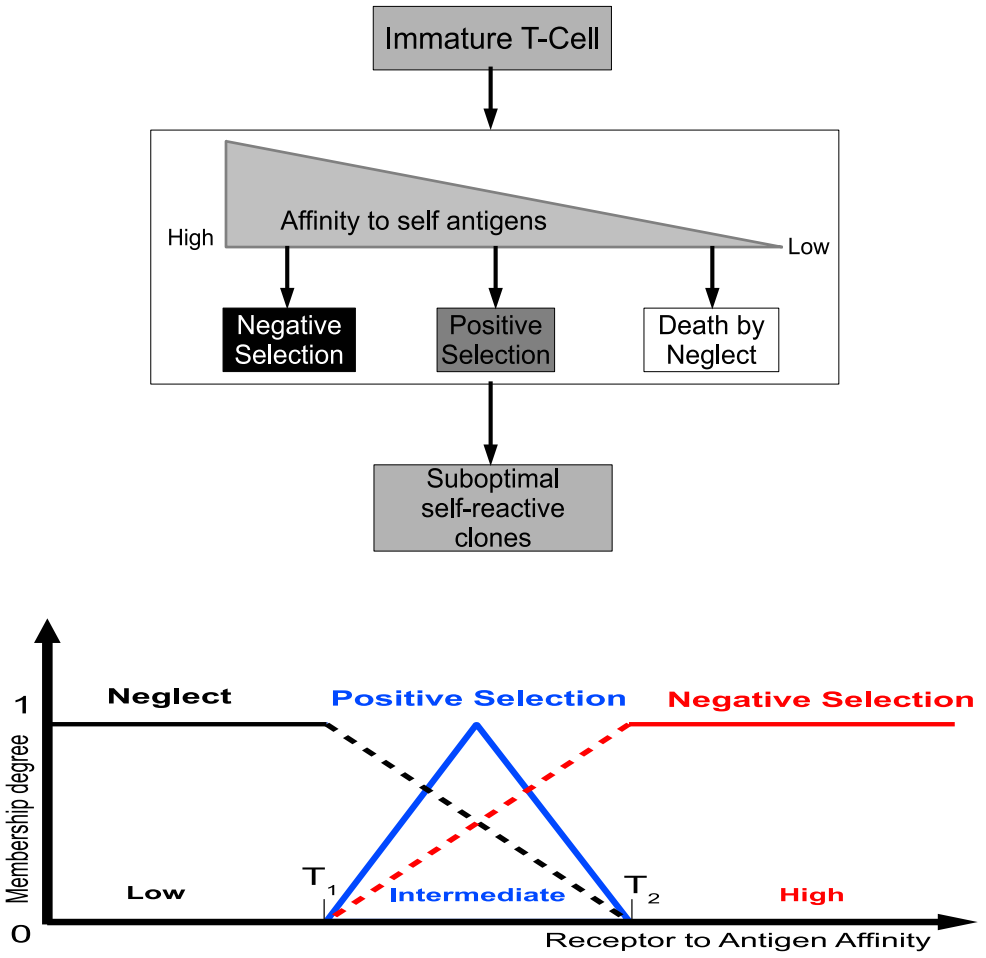


Fig. 4.1: Illustration of the hypothesis of T cell fuzzy recognition according to [Leng and Bentwich, 2002]. The process of *self / nonself* discrimination, their membership functions describing the relationship between the affinity between cell and antigen with a biological reaction of the immune system.

Figure 4.2, based on the model described in Figure 4.1.

Analyzing the model, the fuzzy system considers negative selection process as the allocation of a detector in the region of normal operation and positive selection as the successful allocation of a detector (in the anomaly region), detectors placed in regions considered unfeasible, far away compared to other detectors, suffer a process called death by neglect, i.e. these detectors are considered useless for system monitoring.

Figure 4.3 shows some examples of the algorithm functioning in a two-dimensional space.

Membership functions are generated through two thresholds T_1 and T_2, which are respectively for the positive selection (Rule 3 to rule 2) and negative selection (rule 2 to rule 1),

Tab. 4.1: fuzzy rules used in the antigen recognition system for the generation of detectors.

	Rule	Feedback
1	If *distance* is `low`	Then *response* is `negative_selection`
2	If *distance* is `medium`	Then *response* is `positive_selection`
3	If *distance* is `high`	Then *response* is `death_by_neglect`

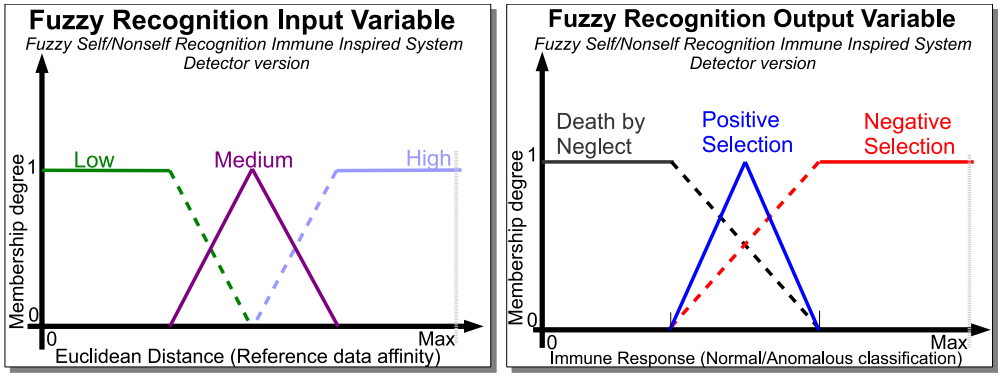


Fig. 4.2: Membership functions for detectors generator version.

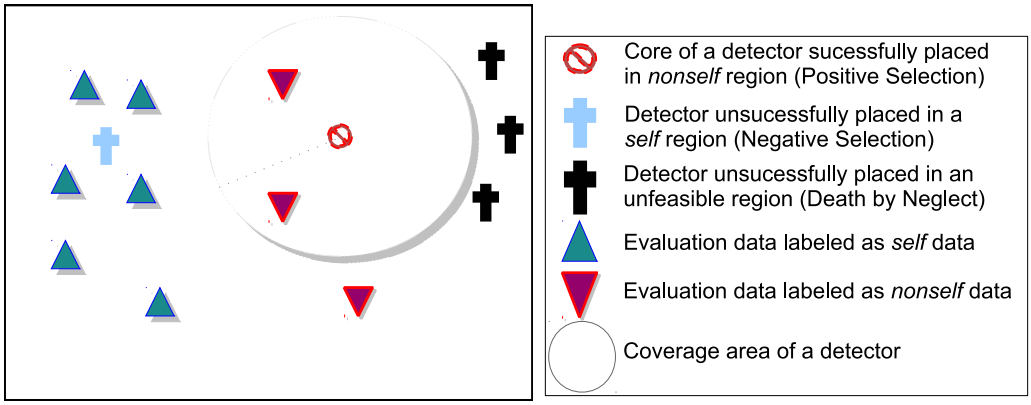


Fig. 4.3: Description of the proposed algorithm in a two-dimensional space.

and being $T_1 < T_2$. The set of thresholds specifying detector borders and the stopping criteria (number of detectors or the same coverage rate) are parameters evaluated by the algorithm, described as in flowchart of Figure 4.4 and also in Algorithm 4.1.

This algorithm can also be used to enhance other negative selection based techniques which employ detectors to assess fault detection in the system.

Algorithm 4.1 Pseudocode of Detector Generation in Fuzzy NSA

```
1: procedure FuzzyNSATraining(Ag_Tr, T_1, T_2)
2:     S ⇐ ∅
3:     while not(StopCriteria) do
4:         D ← Randomize(n)                          ▷ Generate a random n-dimensional point.
5:         parameters ← NegativeSelectionRules(D)    ▷ Calculate parameters based on the NSA version.
6:         for all i ∈ Ag_Tr do
7:             dist_i ← EuclideanDistance(D, Ag_Tr(i))   ▷ Calculate distance of D between Training Data.
8:         end for
9:         bind ← AffinityNSA(min(dist), parameters)   ▷ Calculate affinity based on NSA version.
10:        decision ← FuzzyRules(bind, T_1, T_2)       ▷ Apply fuzzy system.
11:        for all m ∈ Migrated do
12:            if decision = positive_selection then   ▷ Positive Selection.
13:                S ⇐ D                               ▷ Allocate S in Detector Set.
14:            end if
15:        end for
16:    end while
17: return S
18: end procedure
```

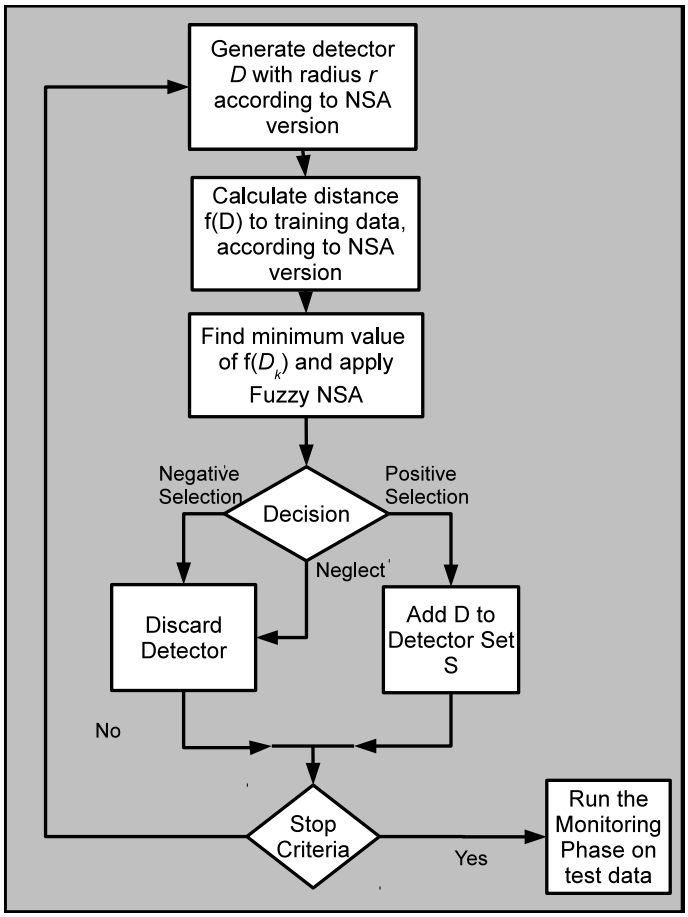


Fig. 4.4: Flowchart describing the steps of Detector Generation in Fuzzy NSA.

4.1.2 Monitoring algorithm

This model serves as a simplification of the negative selection algorithm and uses the Euclidean distance as a anomaly metric, in which the similarity to the training data defines conditions of sampled (validation) data. The fuzzy inference system used will define the data labeling based on the distance between the data and reference. Assuming that outliers may represent anomalous compared to normal data, it is possible to detect anomalies in this way.

The algorithm works fundamentally using the distance between sampling to the nearest reference for labeling the sampling data as normal or anomalous and the fuzzy inference system is similar to the one described in detectors generation algorithm, except for the rule of death by neglect, which is not considered in this approach because the context for its use in this model is still unknown. In this case, the monitoring is reduced to two rules: positive selection and negative selection.

The rules are represented as in Table 4.2. Inputs are fuzzified as membership functions in

trapezoid form, representing the degree distance between data presented and reference data, and outputs are represented by triangular membership functions, which represent the immune response (status of the system). The membership functions are represented in Figure 4.5.

Tab. 4.2: rules used in fuzzy system for monitoring of antigen recognition.

	Rule	Feedback
1	If *distance* is `low`	Then *response* is `negative_selection`
2	If *distance* is `high`	Then *response* is `positive_selection`

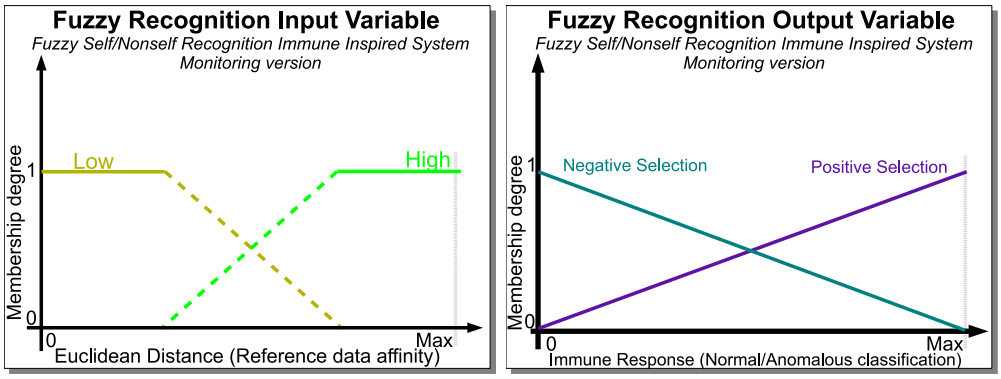


Fig. 4.5: Membership functions for monitoring algorithm version

The algorithm depends on a threshold used to adjust the membership function and to define boundaries between normal data and data anomaly. The threshold is dependent on the problem, because there are cases where the outliers can be quite common.

This algorithm differs from other negative selection algorithms, because there is no need to generate detectors for discovering anomalous processes in a system. The algorithm verifies if test data are sufficiently discrepant for the indication of an anomaly.

The algorithm also relies on a normalization factor of the distance metric, based on a hill function. This factor is used to avoid values out of the range, and is shown in (4.1).

$$\zeta_{Ag_k} = 1 - \frac{Dist(Ag_k, Tr_{nearest})^h}{1 + Dist(Ag_k, Tr_{nearest})^h} \tag{4.1}$$

Where $Dist(Ag_k, Tr_{min})$ is the distance metric between antigen and training samples, usually the Euclidean Distance, and h is the value for the hill function. In all tests performed, $h = 2$ is adopted.

Figure 4.6 shows some examples of the functioning of the algorithm in a two-dimensional space, with the training data functioning as a reference for evaluation of data validation.

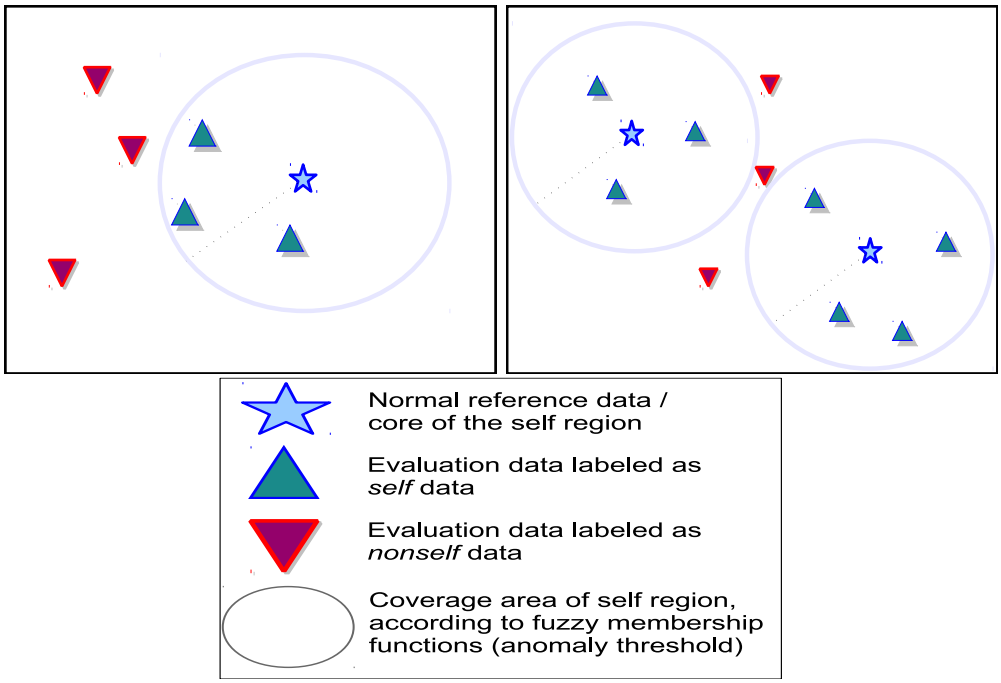


Fig. 4.6: Description of the proposed algorithm in a two-dimensional space.

The method follows that specified in Figure 4.6 and Table 4.2: The membership functions are generated based on a threshold thr. Besides this, reference data (training) and the sampling to be classified (validation) are the evaluated parameters by the algorithm, described as in flowchart of Figure 4.7 and also in Algorithm 4.2.

4.1.3 Simulation Results for detector generator

The algorithms were applied in the case of DC motor presented in [D'angelo et al., 2010] and described in Chapter 2.

The distances between the data and reference data are normalized to 0 to 1 in order to make easier the data processing by fuzzy inference system. In addition, we used the data output of the model, with reference data using 1000 points in continuous normal operation, while each simulation has 3000 points in steady state. Faults occur at the point of each simulation 1000 (1 millisecond of operation). Results are presented in terms of classification rate, as well as delay in detection.

For detectors generation, these thresholds were adopted: $T_1 = 0.15$ and $T_2 = 0.95$ all of them based on significance levels considering the probability of false alarms (T_2 is based on error

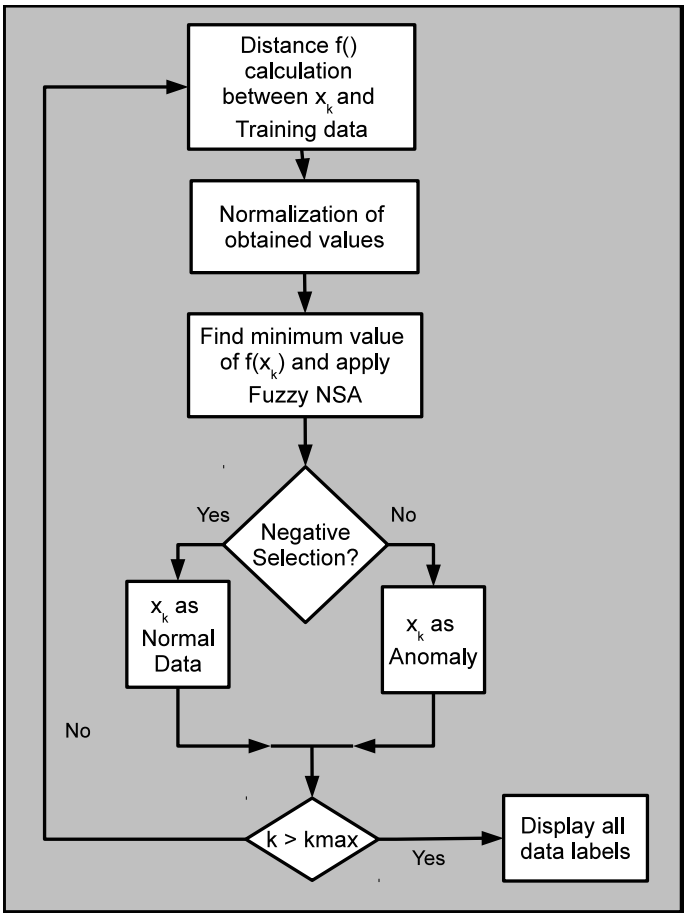


Fig. 4.7: Flowchart describing the steps of Monitoring of Fuzzy NSA.

correlation) or the probability of a detector being placed in an infeasible region (T_1 is based on the coverage through self area distance). The fuzzy system was applied in the V-Detector algorithm presented in [Ji and Dasgupta, 2004a], which uses some mechanisms that may provide high coverage of the nonself area. The self radius is about $r_s = 0.1$, the desired coverage is up to 97.5 % coverage per detector and the other stopping criterion is occurs when 150 detectors are placed or after 250 attempts. The algorithm was run 50 times, as the algorithm places detectors in random locations through positive selection.

The proposed algorithm, according to the results in Table 4.3, is able to detect most faults in the test without false alarms, however, in fault 4, the algorithm was unable to detect few points, The algorithm succeeded to generate most detectors and no detectors have been discarded (Allocated in the region of normal operation). The useless detectors suffer death by neglect, which happened in some cases.

In Table 4.4, we can see the results with the same algorithm, but without the fuzzy inference system for antigen recognition. The purposed system has improved the algorithm performance,

Algorithm 4.2 Pseudocode of Monitoring based on Fuzzy NSA

procedure FUZZYNSAMONITORING(x_{Ts}, x_{Tr}, thr, h)
  for all $i \in x_{Ts}$ **do**
    for all $j \in x_{Tr}$ **do**
      $dist_{(j)} \leftarrow$ EUCLIDEANDISTANCE($x_{Ts}(i), x_{Tr}(j)$) ▷ Calculate distance of Test sample between Training Data.
    end for
    $nearest \leftarrow$ **argmin**($dist$)
    $\zeta \leftarrow 1 - \frac{dist^h_{(nearest)}}{1+dist^h_{(nearest)}}$ ▷ Calculate affinity between all Training Data.
    $decision \leftarrow$ FUZZYRULES(ζ, thr) ▷ Apply fuzzy system.
    if $decision =$ `positive_selection` **then** ▷ Positive Selection.
      $y_i \leftarrow$ `anomaly`
    else ▷ Negative Selection.
      $y_i \leftarrow$ `normal`
    end if
  end for
return y
end procedure

considering that the algorithm was able to detect more fault points than the original algorithm.

4.1.4 Simulation Results for monitoring

For the monitoring algorithm, it is expected to overcome weak points of the detectors generation algorithm. Threshold adopted for use by the fuzzy inference system was $thr = 0.95$.

According to Table 4.5, in all simulations the monitoring algorithm was able to detect faults in the instant in which they occurred, this indicates that the algorithm was able to distinguish the normal points from anomaly points with no false alarms or misdetection.

In fact, the algorithm works on normal data and the same distance in relation to sampled data. Anomaly detection is performed when the data are far from the reference data, through the threshold of the fuzzy system.

This result shows that the approach based on monitoring may be an alternative to the generation of detectors and is promising as the proposed objectives, detecting faults, however, still requires some modifications to achieve the objectives. With its fuzzy nature, other immune-inspired fuzzy inference rules may be implemented in order to provide a more enhanced data processing and its subsequent detection.

Tab. 4.3: Results of tests performed on the generator algorithm detectors.

Scenario	Found points	Delay	False Alarms	Misdetection
Normal	0	-	0%	0%
Fault 1	2001	0	0%	0%
Fault 2	2001	0	0%	0%
Fault 3	2001	0	0%	0%
Fault 4	1994	6	0%	3%
Fault 9	2001	0	0%	0%
Fault 10	2001	0	0%	0%
Fault 11	2001	0	0%	0%

	Generated Detectors	Discarded Detectors (Death by Neglect)	Discarded Detectors (Negative Selection)
Number	83	17	0

4.2 Fault Diagnosis using Participatory Clustering

The participatory clustering algorithm was developed in [da Silva et al., 2007] as an algorithm that uses the method of participatory learning, defined in [Yager, 1990]. The model represents better the functioning of human learning because it contains a mechanism that allows reviewing in learned concepts.

The algorithm is based on two indices: the Compatibility index of data cluster centers, which measures in which group data may be included, and the Alert index, which measures the reliability of the acquired knowledge in each cluster, checking if its structure should be revised, which implies the inclusion of a new group in the system.

In [Lemos et al., 2011], the participatory clustering algorithm has been improved with some mechanisms complementary to compatibility and alert threshold. In Compatibility index, we use a distance metric which uses a scattering matrix to measures the co-variance of the groups, and the threshold definition follows a chi-square distribution. The Alert index calculation is based on a sliding window mechanism that defines how many observations are made in relation to compatibility threshold violations, analyzed by a Bernoulli distribution which have a window size dependent level of significance.

Thus, the participatory clustering algorithm was defined through four influence parameters: a learning rate α which updates the cluster parameters, the window size w that monitors changes in compatibility index, the level of significance λ used in the calculations, and initial scattering matrix Mtx, which defines the creation of new groups.

Tab. 4.4: Results of tests performed on a normal Negative Selection Algorithm, for comparison purposes.

Scenario	Found points	Delay	False Alarms	Misdetection
Normal	0	-	0%	0%
Fault 1	1964	37	0%	18.56%
Fault 2	2001	0	0%	0%
Fault 3	1951	50	0%	2.48%
Fault 4	1994	6	0%	0%
Fault 9	1841	160	0%	8%
Fault 10	2001	0	0%	0%
Fault 11	1961	40	0%	2%

	Used Detectors	Useless Detectors	Discarded Detectors
Number	17	-	0

4.2.1 Description of the Participatory Clustering algorithm

The participatory clustering algorithm is used when the Fuzzy Antigen Recognition Algorithm sends an alarm signal. After the fault event, the system searches the list **c** of the existing clusters and calculates the distance between the detected data x_k and the center c_g of the cluster, and using the scattering matrix Mtx_g information, as shown in (4.2).

$$D(x_k, c_g) = (x_k - c_g)(Mtx_g)^{-1}(x_k - c_g)' \tag{4.2}$$

Thus, the calculation of the compatibility index ρ_g is performed using (4.3).

$$\rho_g = exp\{-\frac{1}{2}D(x_k, c_g)\} \tag{4.3}$$

Then, the ρ_g compatibility index is compared with a threshold $T\rho$, calculated by the chi-square distribution χ^2 with a significance level λ and depends on the number of dimensions of input data n, as shown in (4.4).

$$T\rho = exp\{-\frac{1}{2}\chi^2_{n,\lambda}\} \tag{4.4}$$

A boolean variable O_k stores the value resulting from comparing ρ_g and $T\rho$, then the sum v of w last observations in O_k value is calculated. The alert index a_g is calculated through the Bernoulli distribution in (4.5). If the number of points is greater than the window w or equal

Tab. 4.5: Results of tests made with the monitoring algorithm.

Scenario	Found points	Delay	False Alarms	Misdetection
Normal	0	-	0%	0%
Fault 1	2000	0	0%	0%
Fault 2	2000	0	0%	0%
Fault 3	2000	0	0%	0%
Fault 4	2000	0	0%	0%
Fault 9	2000	0	0%	0%
Fault 10	2000	0	0%	0%
Fault 11	2000	0	0%	0%

to it, otherwise the rate of alert is 0.

$$a_g = \binom{w}{v}\lambda^v(1-\lambda)^{(v-w)}, v = 0, ..., w \tag{4.5}$$

The alert threshold T_a, used to generate new clusters, is defined through (4.6).

$$T_a = 1 - \frac{\lambda}{w} \tag{4.6}$$

Once compatibility is compared to the indexes of the nearest cluster g and the alert index a_g with their respective thresholds, the algorithm can generate a new cluster or update an existing cluster g including the new point and by modifying center position and the scattering matrix Mtx_g. The factor G_g is calculated to update existing clusters.

$$G_g = \alpha({\rho_g}^{1-a_g}) \tag{4.7}$$

$$c_g = c_g + G_g(x_k - c_g) \tag{4.8}$$

$$Mtx_g = (1 - G_g)(Mtx_g - G_g(x_k - c_g)'(x_k - c_g)) \tag{4.9}$$

However, in some cases, the algorithm can create redundant clusters. To minimize this problem, as new clusters a and b are created, these are compared, as in (4.10).

$$D(c_a, c_b) = (c_b - c_a)(M_a)^{-1}(c_b - c_a)' \tag{4.10}$$

Likewise, the distance between clusters is calculated by (4.3), using the generated value in (4.10). If this metric is greater than the threshold $T\rho$, a and b are united.

With the clustering algorithm used in the system used at work, it can distinguish the faults occurred to aid in the diagnose task. It is noteworthy that only the data classified by the system as faults pass through the stage of generating and updating of the groups by the clustering algorithm participatory, which can also update the structure of groups as new data is entered.

In short, the system can be described using the flowchart in Figure 4.8 and in Algorithm 4.3.

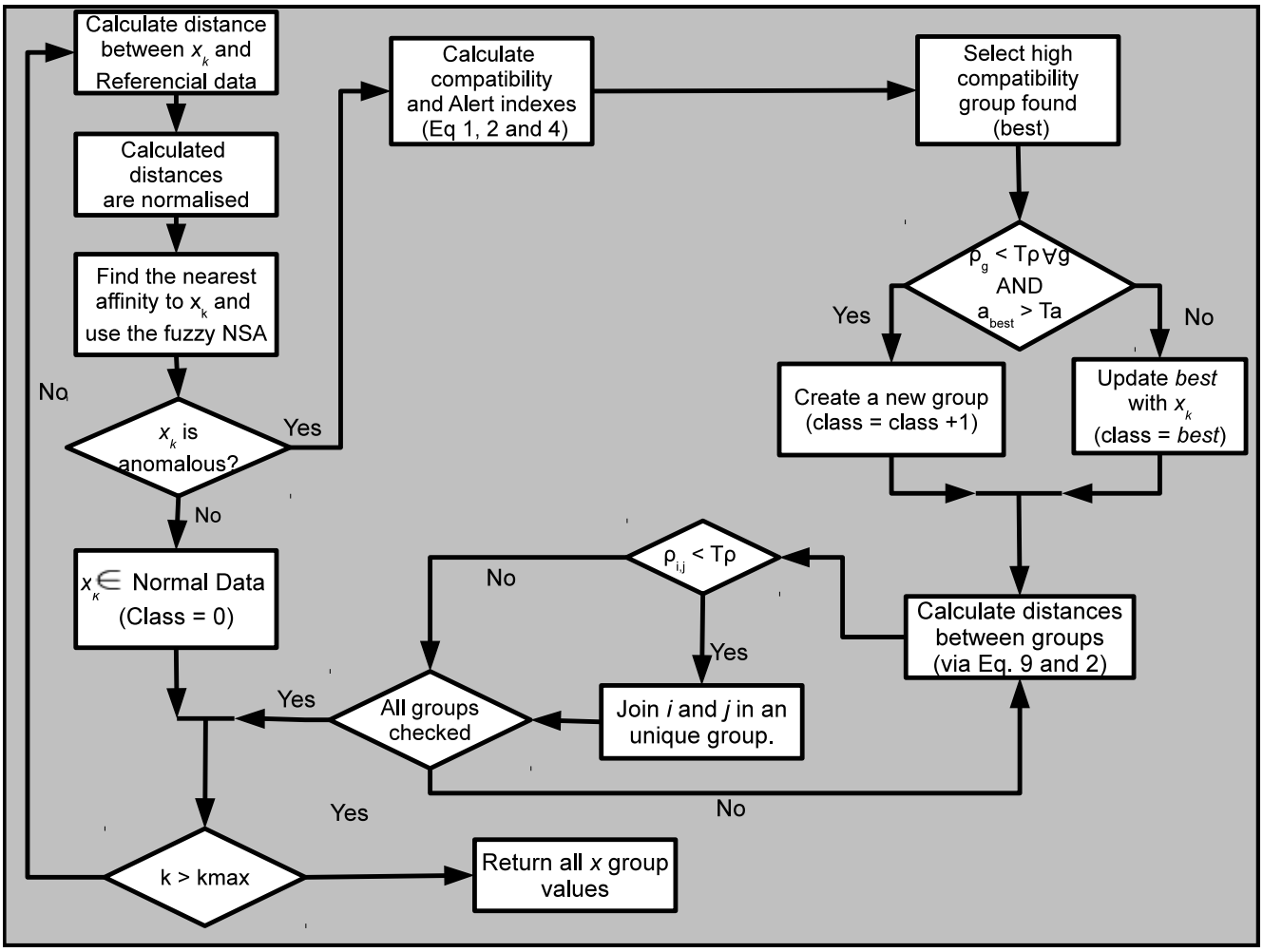


Fig. 4.8: Flowchart representing the participatory clustering applied after NSA detection.

This algorithm will be applied to the same scenario presented in section 4.1.2, where the fuzzy antigen recognition monitoring algorithm was used to fault detection alarms.

4.2.2 Application on the fault diagnosis problem

The fuzzy antigen recognition system with diagnosis based on participatory clustering is applied to DC Motor experiments. The algorithm will use the four fault data in sequence as data

Algorithm 4.3 Pseudocode of the Participatory Clustering applied to the Fuzzy NSA

procedure PARTICIPATORYCLUSTERINGFAULTDIAGNOSIS($x_{Ts}, x_{Tr}, thr, h, \alpha, \beta, w, \lambda, Mtx_{1st}$)
  $ng \leftarrow 1$
  $c_1 \leftarrow$ CREATENEWGROUP(x_k, Mtx_{1st})
  $T_a \leftarrow 1 - \frac{\lambda}{w}$
  $T\rho \leftarrow exp\{-\frac{1}{2}\chi^2_{n,\lambda}\}$
  for all $k \in x_{Ts}$ **do**
    $y_k \leftarrow$ FUZZYNSAMONITORING($x_{Ts}(k), x_{Tr}, thr, h$)
    if $y_k \leftarrow$ `anomaly` **then**
      for $g \leftarrow 1$ to ng **do**
        $dist_{(g)} \leftarrow$ DISTANCEMETRIC(x_k, c_g, Mtx_g)
        $\rho_g \leftarrow \mathbf{exp}\{-\frac{1}{2}dist_{(i)}\}$
      end for
      $b \leftarrow \mathbf{argmin}(\rho)$
      $o_k \leftarrow$ ISFALSE($dist_{(g)} < \chi^2_{n,\alpha}$)
      $a_{best} \leftarrow$ OBSERVATIONVIOLATIONS(λ, w, o)
      if $\rho_g < T_\rho$ **and** $a_{best} > T_a$ **then**
        $ng \leftarrow ng + 1$
        $\{c_{ng}, Mtx_{ng}\} \leftarrow$ CREATENEWGROUP(x_k, Mtx_{1st})
        $idx \leftarrow ng$
      else
        $\{c_b, Mtx_b\} \leftarrow$ UPDATEGROUP($x_k, c_b, Mtx_b, \beta, \rho_b, a_b$)
        $idx \leftarrow b$
      end if
      for $i \leftarrow 1$ to ng **do**
        $dist \leftarrow$ DISTANCEMETRIC(c_i, c_{idx}, Mtx_{idx})
        $\rho_i \leftarrow \mathbf{exp}\{-\frac{1}{2}dist\}$
        if $\rho_g < T_\rho$ **then**
          $merge \Leftarrow i$
        end if
      end for
      for all $i \in merge$ **do**
        $c_{idx} \leftarrow$ MERGEGROUPS(c_i, c_{idx}, Mtx_{idx})
        UPDATEGROUPINDEX(C, idx)
      end for
      $merge \Leftarrow \emptyset$
      $C_k \leftarrow idx$
    else
      $C_k \leftarrow 0$
    end if
  end for
return y, C
end procedure

sampled (with a total of 12,000 points), using 1000 points of normal operation as reference data.

Using the threshold thr of the fuzzy system, the parameters of the clustering algorithm should be defined as the rate of learning α, the window size w, the significance level λ and the initial values of the matrix Mtx scattering.

For these tests, we set the following parameters, $thr = 0.95$, $\alpha = 0.1$ and the initial matrix M has been obtained covariance of the starting point, since values of the covariance matrix groups can make a scattering singular matrix along the iterations.

The values of w is test dependent, showing situations in which the algorithm has good performance, when the values of λ vary the values of w also vary, because the lower is the level of significance, the larger should the window size be, considering that lower window values can generate allocation of data in wrong clusters, while it can also happen spurious generation of many clusters for the same fault case, in addition, any inappropriate combination of values can generate a very large number of clusters for the same fault.

Table 4.6 shows the result with $w = 1000$ and $\lambda = 0.005$, the values in parentheses are the clusters indicated by the algorithm, some values that classified as a fault of the group, while Table 4.7 shows the result with $w = 2000$ and $\lambda = 0.0001$, which led to one more group.

Tab. 4.6: Results for $w = 1000$ and $\lambda = 0.005$.

Scenario	Hits	Errors	Clusters
Normal	4000	0	1 (0)
Fault 1	2000	0	1 (1)
Fault 2	1983	17 (1)	1 (2)
Fault 3	1983	17 (1)	1 (3)
Fault 4	1983	17 (1)	1 (4)

Tab. 4.7: Results for $w = 2000$ and $\lambda = 0.0001$.

Scenario	Hits	Errors	Clusters
Normal	4000	0	1 (0)
Fault 1	1000 (1) 1000 (2)	0	2 (1 and 2)
Fault 2	2000	0	1 (3)
Fault 3	2000	0	1 (4)
Fault 4	2000	0	1 (5)

These values indicate that the performance is close to the desirable, where the goal is to generate the smallest number of clusters as possible, so the algorithm can distinguish each fault as correctly as the clusters are being generated by the algorithm.

The best result was obtained in Table 4.8, where it was possible not only generate all clusters correctly, but also allocate the data correctly in the appropriate form in this experiment, the window size is 3000, corresponding to the number of simulation points.

Tab. 4.8: Results for $w = 3000$ and $\lambda = 0.0005$.

Scenario	Hits	Errors	Clusters
Normal	4000	0	1 (0)
Fault 1	2000	0	1 (1)
Fault 2	2000	0	1 (2)
Fault 3	2000	0	1 (3)
Fault 4	2000	0	1 (4)

The results indicate that a combination of values of w and λ, as well as a value that is close to characteristics of the data. Table 4.9, there was the similar, but with an error in one of the faults. The situation ideal has been achieved with a combination of values, however, as a combination of Table 4.10 can cause an undue generation of many clusters in the same one.

Tab. 4.9: Results for $w = 4000$ and $\lambda = 0.0005$.

Scenario	Hits	Errors	Clusters
Normal	4000	0	1 (0)
Fault 1	2000	0	1 (1)
Fault 2	1999	1 (1)	1 (2)
Fault 3	2000	0	1 (3)
Fault 4	2000	0	1 (4)

Tab. 4.10: Results for $w = 3000$ and $\lambda = 0.0001$.

Scenario	Hits	Errors	Clusters
Normal	4000	0	1 (0)
Fault 1	2000	0	1 (1)
Fault 2	2000	0	1 (2)
Fault 3	2000	0	1 (3)
Fault 4	2000	0	32 (4 to 36)

The results in Table 4.10 also show that the generation of clusters is highly sensitive to the level of significance, which can confuse the system by creating many clusters to a single anomaly.

Analyzing the results, it is confirmed that the values of the window and level of significance are dependent on each other and dependent on the problem studied and are in fact important to distinguish between faults.

Chapter 5

Other Immunological Models and Their Application to Fault Detection and Diagnosis

5.1 Challenging points

The new approaches have significant representation for anomaly detection problem, with a greater contextualization of data for a given application. Such alternatives, however, may face some limitations regarding the context analysis of the problem: prior expert knowledge should be suitable as represented by these algorithms. In many anomaly detection problems, such as FDI applications, such representation may not be trivial.

In the Fault Detection and Isolation (FDI) particular case, there are some features that imply challenges in the approach due to difficulties of the adequacy of the data to the problem. In some cases, the use of redundant models is quite common and according to [Chow and Willsky, 1984], two steps may be defined in the task of FDI: the generation of residuals through these models and the decision making regarding system state. The first task is the use of models to generate relevant data and the second is the analysis of information represented by residuals.

The immune-inspired algorithms reviewed considered in Chapter 3 would be responsible for decision making tasks after residuals generation, which would be considered as a suitable representation for expert knowledge required by these algorithms and abstracted translation of input signals. However, these representations can be redundant for these algorithms and may result in high computational costs.

Since these approaches were designed to require a more abstract representation for anomaly

detection, such information required for a given event to be classified as a faulty behavior may not be trivial to obtain, depending on the dynamic system.

These algorithms usually adopt some representations of signals corresponding to the evaluation of dynamic system behavior through prior knowledge. Obtaining this model is one of the steps implied in the development of FDI systems.

For a dynamic system, antigen-based data correspond to the output data, and may be evaluated according to the behavior. In DCA and TLR, the correlation mechanisms between signals and antigens can be interpreted as the process classification scheme.

However, many of these systems are not consistent with the representation by these algorithms required and often this model must be inferred using the available data.

This scenario can be summarized by Figure 5.1, which also describes the organization related to monitoring systems based on the immune-inspired techniques further presented in this chapter.

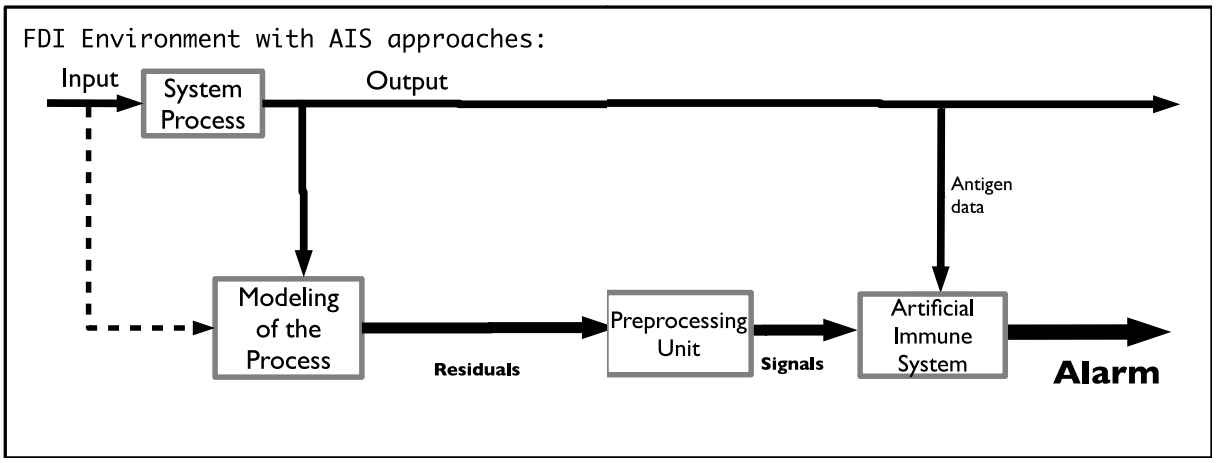


Fig. 5.1: Fundamental steps of Fault Detection tasks.

The anomaly detection inspired by the self-nonself discrimination applied to fault detection is based on direct evaluation of the antigen represented by feature space considering two important characteristics: the need for training data, implied by the process negative and/or positive selection, and similarity measures for evaluation of the data as the space characteristics.

Despite these facilities, these algorithms have problems arising from the lack of context in relation to the application environment and the computational cost provided by the evaluation of these algorithms, making the implementation unfeasible in real time applications.

It is considered that immunological models have, in the transcription of AIS features that represent transitional links considering how to handle input data and treatment of the problem of detecting anomalies. In Figure 5.2, such features are defined as a way of understanding how

AIS can be applied to Anomaly Detection problems, such as Fault Detection.

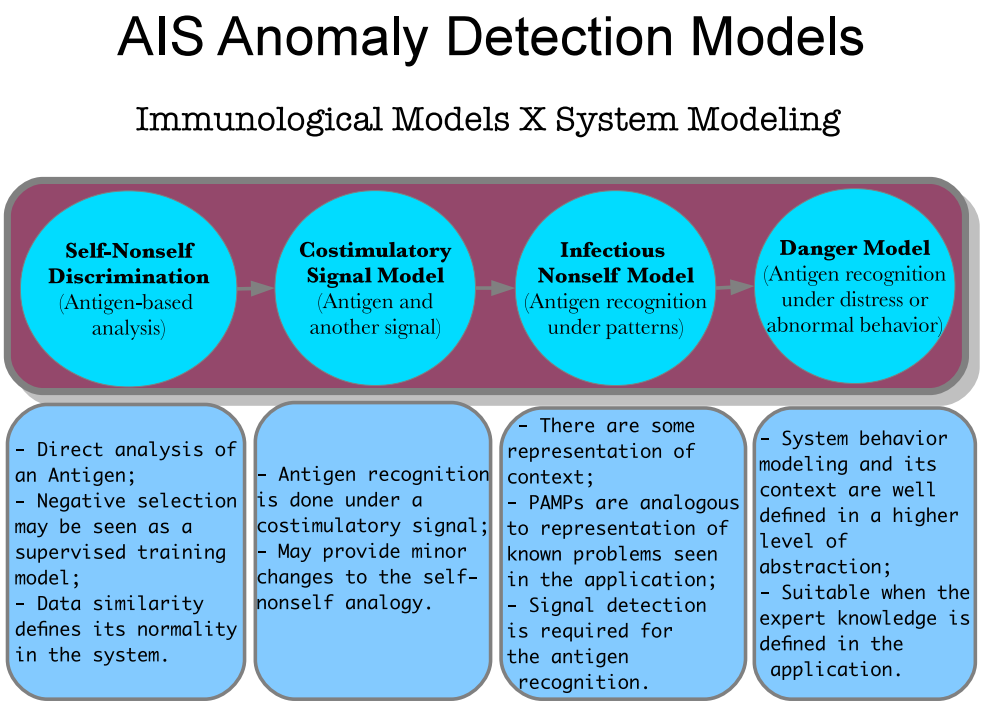


Fig. 5.2: Relationship among immunological models that can be considered in the development of new immune-inspired systems.

With these considerations, it is possible to represent immune-inspired approaches according to the following principles.

- The Infectious Nonself and Danger models should consider the use of signals, usually defined by expert knowledge;
- In Self-Nonself Discrimination in association with the training of machine learning algorithms is inherent, since the Self patterns should be known;
- The signals used by AIS algorithms must adequately represent the current status of important events to the objective of the problem;
- Prior knowledge models can also be obtained through training based methods (ANN, for example);
- The representation of antigens is not a mandatory feature in algorithms based on Infectious nonself or Danger models (as in [de Almeida et al., 2010]).

Importantly, some of these assumptions are interpreted according to the adopted immunological model for the development of a technique. For FDI problems, some abstractions are necessary for the implementation of such algorithms.

Some techniques for processing information used in this work will be presented to generate the signals interpreted and used by these AIS approaches.

5.1.1 Antigen modeling

Most dynamic systems have only the input and output variables as available information without markers or identifiers. However, there are some ways to deal with this issue.

Since the goal of FDI problems is the classification of fault data, output data can be used as antigens, which will simply indicate the current state of the system.

The disadvantage of this principle comes from the problem dimensionality. However, considering data storage, each information must be identified by a code, as in a database system. This code, which represent the antigen used by the algorithm, can be generated by several ways.

Another possible method is to use similarity metrics and consider zero as the exact location of the antigen, in addition, searches can be approximated by a threshold based similarity of the antigen, as demonstrated in the examples using the equation (5.1), however, the problem of this approach is precisely the overlap of some antigens in certain cases.

$$\sum_{i=1}^{N}(Y_{(k,i)} - Ag_i)^2 <= thr \tag{5.1}$$

Antigen overlap is similar to the approximate recognition seen in Self-nonself discrimination, the adoption of this data format using the feature space becomes intuitive, and the overlap is regarded as a similarity data, which has been used in the STLR algorithm in [Nejad et al., 2012].

However, if the antigen is used as an identifier, a discretization process in data may be considered or even the ID can be associated with antigen data.

In fact, the antigen processing of these algorithms is important in terms of correlation with the signals to evaluate system behavioral aspects. In AIS based on the Infectious nonself model the antigen can be considered in training or procedural rules, the signal can be modeled through these mechanisms.

In the Danger Model, signals modeling is the most important aspect. On the issue of FDI, it is one of the challenges of application modeling. This point will be further discussed, considering some important information regarding processing and practicality.

5.1.2 Signal modeling

There are two options of signal modeling: using a quantitative model as a reference, such that the immune inspired algorithm acts as a supervisor, or measuring variations between data output between past and current instants.

In any case, the information should be pre-processed so that the anomaly will be accurately detected. The following aspects should be considered:

- Adequacy of available information in the application;
- Data processing with time and space properties;
- Evaluation of the data quality and relevance.

Besides these there are many other aspects that can be crucial to a successful anomaly detection, such aspects can also be included within these mentioned as a detection delay due to sampling problems, for example.

Some alternatives for the signals modeling applied to the immune-inspired fault detection in dynamic systems will be further presented.

Using Redundancy Models

A redundancy model has the advantage of being robust to noise and allows other ways of interpreting the data, and it can be used for periodic time series. This approach is characterized by the use of residuals as the expert knowledge interpretation of the immune-inspired algorithm and their conversion to required signals.

In TLR algorithm, a signal is modeled by the square error of the estimated value by the observer states relative to the value observed at the output of the dynamic system, according to (5.2).

$$Signal_{(k)} = (y_{(k,i)} - \hat{y}_{(k,i)})^2 \tag{5.2}$$

The signal is a binary value that characterizes the signal was perceived or not by APCs, therefore, this condition is checked in (5.3), through a threshold thr, corresponding to the maximum value allowed by the residual, to be considered in the training algorithm.

$$SeenSignal \leftarrow Signal_{(k)} \geq thr \tag{5.3}$$

In DCA, the basic formulation requires the use of two signals which verify system conditions, considering the information obtained by the observer .

Thus, the problem safe signal (SS) is similar to the one required by TLR Algorithm, but without the threshold, as in (5.4), and danger signal (DS), which considers the conditions of a possible faulty state, is calculated through the absolute value of variations in residue considered in (5.5).

$$SS_{(k)} = Signal_{(k)} \tag{5.4}$$

$$DS_{(k)} = \begin{cases} SS_{(k,i)} - SS_{(k-1,i)}, & SS_{(k,i)} > SS_{(k-1,i)} \\ 0, & SS_{(k,i)} \leq SS_{(k-1,i)} \forall i \end{cases} \tag{5.5}$$

The redundancy models has the advantage of requiring less details on the system, however, has many disadvantages: Using these models to generate signals, algorithms can treat data and generate alarms but it may reduce the utility of these algorithms. Furthermore, the use of many tools can lead to high computational cost in some cases.

An analytical model can ease the FDI problem solving, considering that the system is observable and data collection is trivial, regardless how to obtain the model.

The possibility of obtaining data without using the redundancy models will be further studied, as these methods will take advantage only from the output of dynamic system.

Using output differential information

Data extraction from variations in output data of a dynamic systems may correspond to a practical alternative for data evaluation.

This solution has some advantage, such as using only data from the system without redundancy models and using it in the immune-inspired approaches. However, the generation of such signals in many cases may be a difficult task, subject to some issues of extracting data in engineering problems, such as noise, for example.

For TLR algorithms, which relies on antigen processing for the definition of signals or their rules, the problem is only regarding the required signals for the fault detection task. In DCA case, however, the problem is regarding the quantitative and qualitative features of each signal, since the detection is entirely dependent on their behavior.

The most intuitive signal that can be considered is the Euclidean distance between data from an instant k compared to its predecessor, according to (5.6). This metric variation considers that a high value should indicate that the dynamic system has an anomalous behavior.

$$Signal_{(k)} = \sum_{i=1}^{N} (X_{(k,i)} - X_{(k-1,i)})^2 \tag{5.6}$$

However, considering the set of null hypothesis of Table 5.1:

Tab. 5.1: Null hypothesis regarding signal variations.

Hypothesis	Description
H1	A signal defined algebraically based on variations of a dynamic system is applicable in any case.
H2	The presence of noise in the system does not alter significantly the evaluation of AIS algorithms.

Consider a variation based on step functions whose impulse response results in the changing values, as shown in Figure 5.3. The signal conversion in (5.6) has resulted as expected.

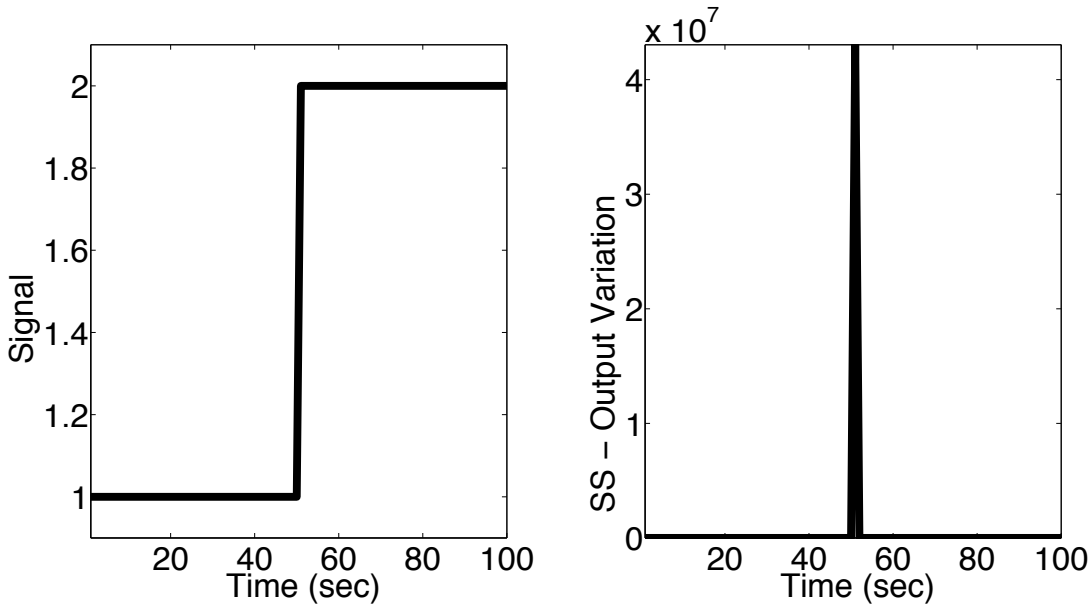


Fig. 5.3: Example of a converted variable in the safe signals.

However, if we consider a periodic signal, the behavior of the proposed metric will be significantly different from the expected, as shown in Figure 5.4. Rejecting H1, a different formulation for this case is necessary.

$$X(k) = \sin(k/50) \tag{5.7}$$

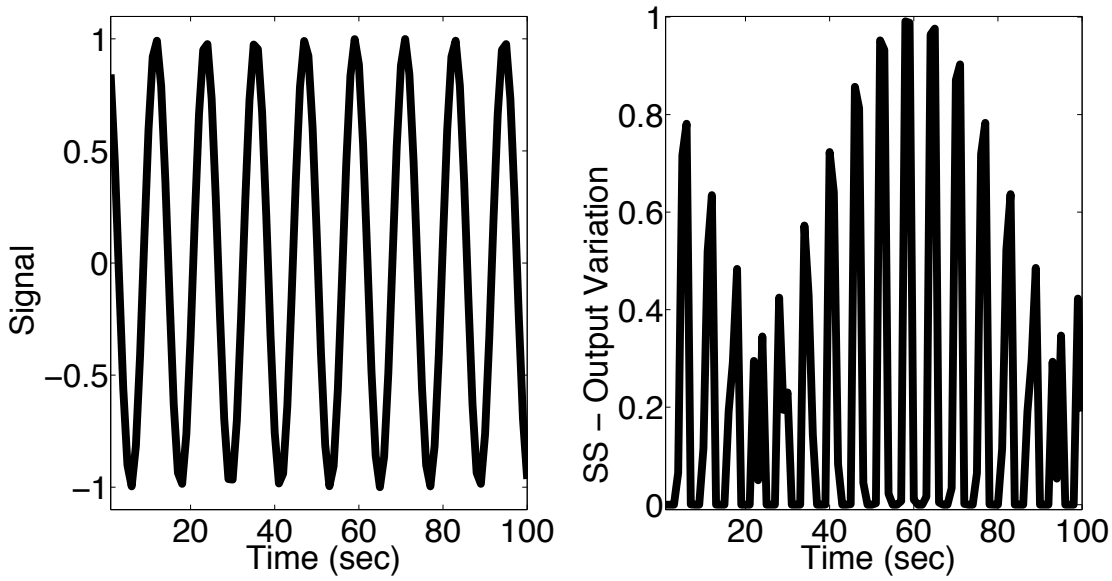


Fig. 5.4: Example with periodic signals (5.7) which invalidates H1.

Another recurring problem in dynamic systems is the noise issue. It is assumed a secondary danger signal based on the safe signal, considering the weighted average of the earlier values, according to (5.8).

$$DS_{(k)} = \sum_{kk=1}^{k} SS_{(k)} - \frac{W_{(kk)}}{k} \tag{5.8}$$

$$W_{(k)} = \frac{k - SS_{(k)}}{k - SS_{(argmax)}} \tag{5.9}$$

Consider the same signal of Figure 5.3, the signal behaves as described in Figure 5.5, which possibly measures a change indicator. However, the situation in Figure 5.6 is shown, considering a noisy signal.

Figure 5.6 shows that the noise feature affects most values of danger signals, leading to the rejection of H2, as the metric is not robust to noise.

The classification of noisy data was considered in [Gu et al., 2011], in which some tests using a supervised algorithm were performed. The main problem is to produce input signals that are robust to noise effects in the preprocessing step.

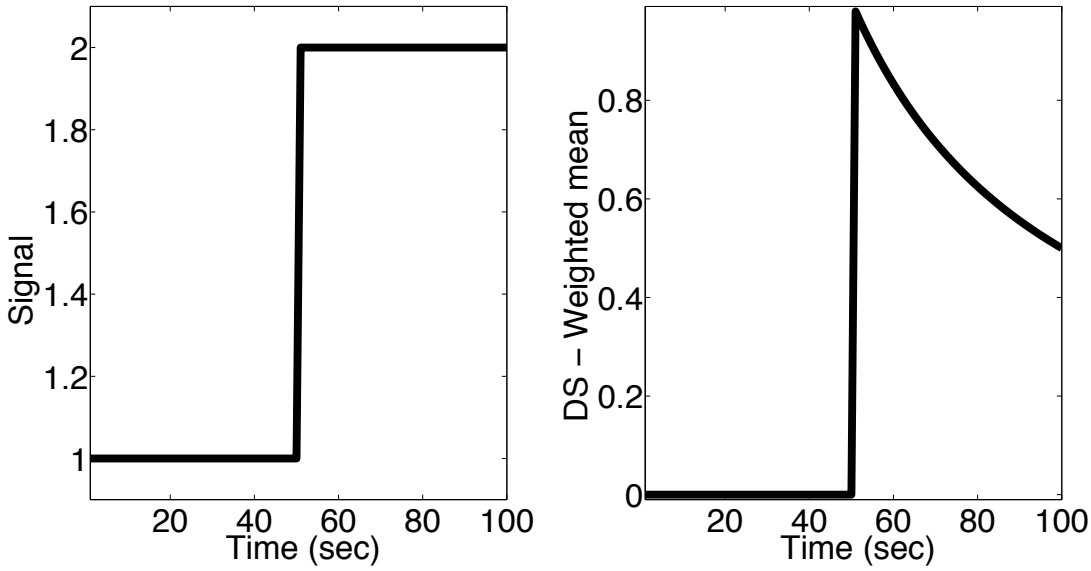


Fig. 5.5: Example of a converted variable in the danger signals.

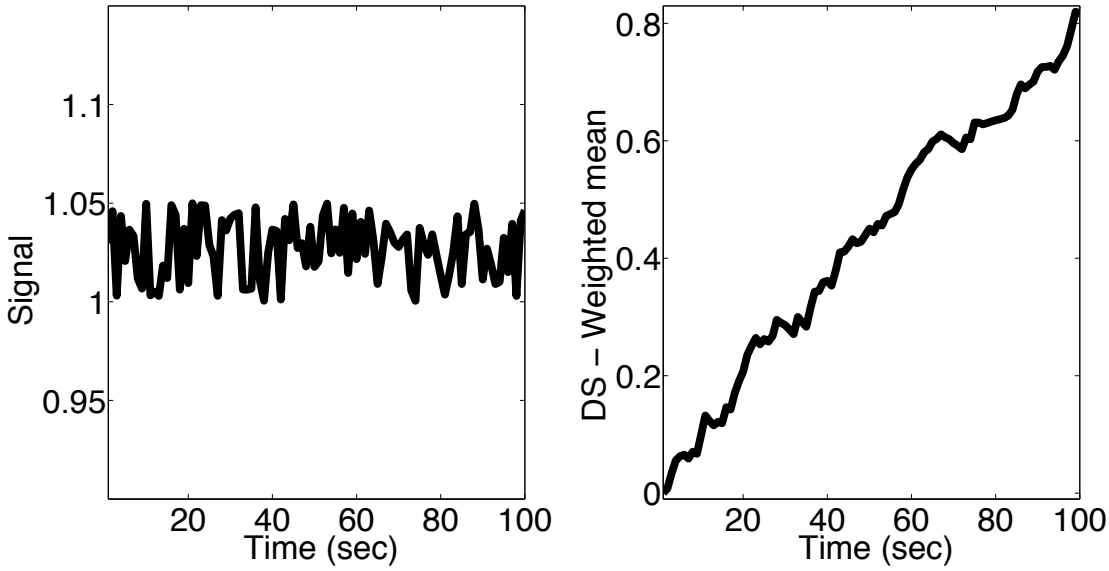


Fig. 5.6: Analysis of a noisy signal converted to danger signal metric.

5.2 Data processing

5.2.1 Normalization

The step of data normalization is a factor of great importance, especially in generation of numerical input signals, which follow certain values.

One way to normalize the signals is to adopt ranges of values for them, as an example in (5.10) valid for PAMP and Danger signals.

$$DS_{(k)} = \begin{cases} 0, & DS_{(k)} < DS_{min} \\ \frac{DS_{(k)} - DS_{min}}{DS_{max} - DS_{min}}, & DS_{min} < DS_{(k)} < DS_{max} \\ V_{max_d}, & DS_{(k)} > DS_{max} \end{cases} \tag{5.10}$$

In these equations, DS_{min} e DS_{max} are thresholds and V_{max_d} is the maximum value of signal range, during k instant.

For safe signals, the process is different, as higher values indicate that system may be operating in normal conditions, so these values have to be inverted as at the example in (5.11). Importantly, V_{max_s} and V_{max_d} may be different according to each problem.

$$SS_{(k)} = \begin{cases} V_{max_s}, & SS_{(k)} < SS_{min} \\ \frac{DS_{max} - SS_{(k)}}{SS_{max} - SS_{min}}, & SS_{min} < SS_{(k)} < SS_{max} \\ 0, & SS_{(k)} > SS_{max} \end{cases} \tag{5.11}$$

In addition, as the safe signal has a very large suppressive effect, output calculation must reflect these factors in order to provide better performance.

Normalization of signals provides a well organized and finite range of data. For DCA algorithms it results in structured and non biased data processing, as well as a proper cell lifetime distribution and signals with reasonable values, without outliers.

The TLR algorithm also relies on signal normalization, these should be not only finite, but also discretized. This factor implies the need of discretization signals, and normalization. All these signals are considered in the rules applied to TLR and whose signals unseen in training will be considered a possible anomaly in the algorithm. On DCA, discretization of data is not required, and to solve this problem of TLR algorithm, processing rules are used as further described.

5.2.2 Data sampling

The DCA, being based on cell population, should consider the sampling factor during the pre-processing step, since these cells can collect antigens during the algorithm processing time.

Furthermore, it is estimated that the algorithm processes the input signals by approximately 1 second. In a shorter sampling, DCA loses in performance due to the delays inherent in runtime

cells processing.

The observation time T_o of a dynamic system is considered, from the data obtained. The DCA should process the data in a sampling time T_s, which must satisfy the condition of (5.12) for the correct processing of the algorithm.

$$T_s \geq T_o \tag{5.12}$$

For example, a dynamic system operates $T_o = 1ms$, such as the DCA has default $t_s = 1s$, sampling should contain 1000 observable points. For instant $k = 0$, the first point of the sample is used, then for $k = 1$ is applied from 1 to 1001 point, and signal is generated from these information.

It is stipulated that the ratio T_o and T_s should not be smaller, because in this case the DCA will have a reduced performance, neither larger, to minimize delays in detection.

Besides its importance in processing the DCA, there is another factor: other signals based on the input samples can be generated from sampling, such as some statistical resources for example.

TLR algorithm does not have an explicit definition on temporal factor, although the method can be similarly employed. In this work, sampling is restricted to the DCA, while TLR is employed by iterations.

Antigen multiplier and interpolation

A particular case of sampling in which multipliers are applied to the fault points in a range of values between $\mathbf{X_k}$ e $\mathbf{X_{k-1}}$. Antigens are replicated or interpolated to allow cells to analyze them, once exposed by signals.

This procedure is applied in cases where $T_s = T_o$.

Another way to amplify antigen sampling to be considered is the Sliding Window mechanism. As most fault detection problems are considered as time series representations, each sample can be collected multiple times as information required. This mechanism has several purposes, such as reproducing observed patterns and to improve performance.

An example of antigen sampling by sliding window mechanisms is shown in Figure 5.7.

5.2.3 Data processing applied to signals

The signals used by immune-inspired algorithms must correspond properly to the problem in which the algorithm is being applied. These algorithms have differences concerning the way how these signals are processed:

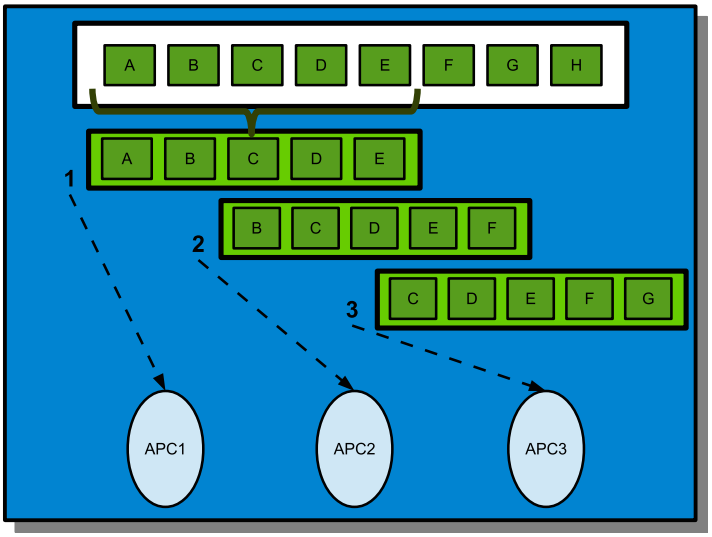


Fig. 5.7: Example of sliding window mechanisms applied to antigen data.

- In Toll-Like Receptor algorithms (TLR and STLR), the signal is evaluated for its presence in Boolean form, 0 for signal absence and 1 for signal presence, as specified in [Aickelin and Greensmith, 2007]. These signal are indicative of abnormal activity and are analogous to PAMPs.

- In DCA, each signal is numerical and they have specific and well-defined categories, being converted to output signals based on weights whose calculation defines the influence of input categories in each output. This processing is described by a matrix, according to [Greensmith, 2007]. In the deterministic version [Greensmith and Aickelin, 2008], this calculation is simplified.

- The algorithm in [de Almeida et al., 2010] considers two signals, which are based on fuzzy processing and whose output is based on a defined mathematical model for fault alarm calculus.

Such processing can be used both to combine some signals that have complementary features, and in terms of adequacy of data to a certain algorithm. The processing of DCA does not require a rigorous use of these mechanisms. For the other algorithms, one of these processing can be defined:

- Direct, with the definition of thresholds for the signal, once necessary;

- Fuzzy, based on inference rules and language processing.

These processing forms are further discussed. Importantly, these processing activities are related to the interaction between the signals and detection agents (APCs), analogous to receptors in a cell. These models are similar to signal receptors by APCs.

Direct Processing

In this processing model, processing rules will always be based on thresholded values and the produced output signal will be binary, where its value is related to the presence of a certain signal.

This type of processing is based on `If-Then-Else` rules, and depending on the need, all rules are aggregated in common, processed by the logical operator `OR`. Figure 5.8 shows an illustrative example with a flowchart.

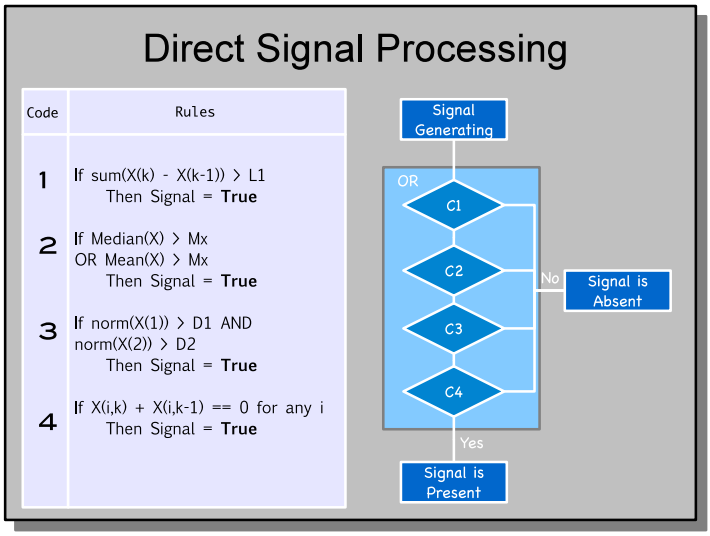


Fig. 5.8: An illustrative example of direct rule processing.

This is the type of processing algorithms as adopted by TLR in [Twycross et al., 2010] with description also in [Aickelin and Greensmith, 2007] mentions the processing as a signal presence indicator, a condition of APCs receptor activation, all rules are considered in this processing regardless of relevance or influence on signal generation.

Fuzzy Processing

The fuzzy processing method combines elements of the other processes, based on the use of fuzzy set theory and the use of rules defined by the membership functions characterizing relations between signals and an output.

The variable type generated by the method is defined by categorical attributes of rules developed through membership functions and fuzzy operators. According to inference mechanisms, numeric variables can also be generated by this method.

The rules used come from the membership functions associated with dynamic system modeling, as in the example of Figure 5.9 which shows the association between membership functions, rules and output processing, corresponding if those signals have been seen (in TLR algorithm).

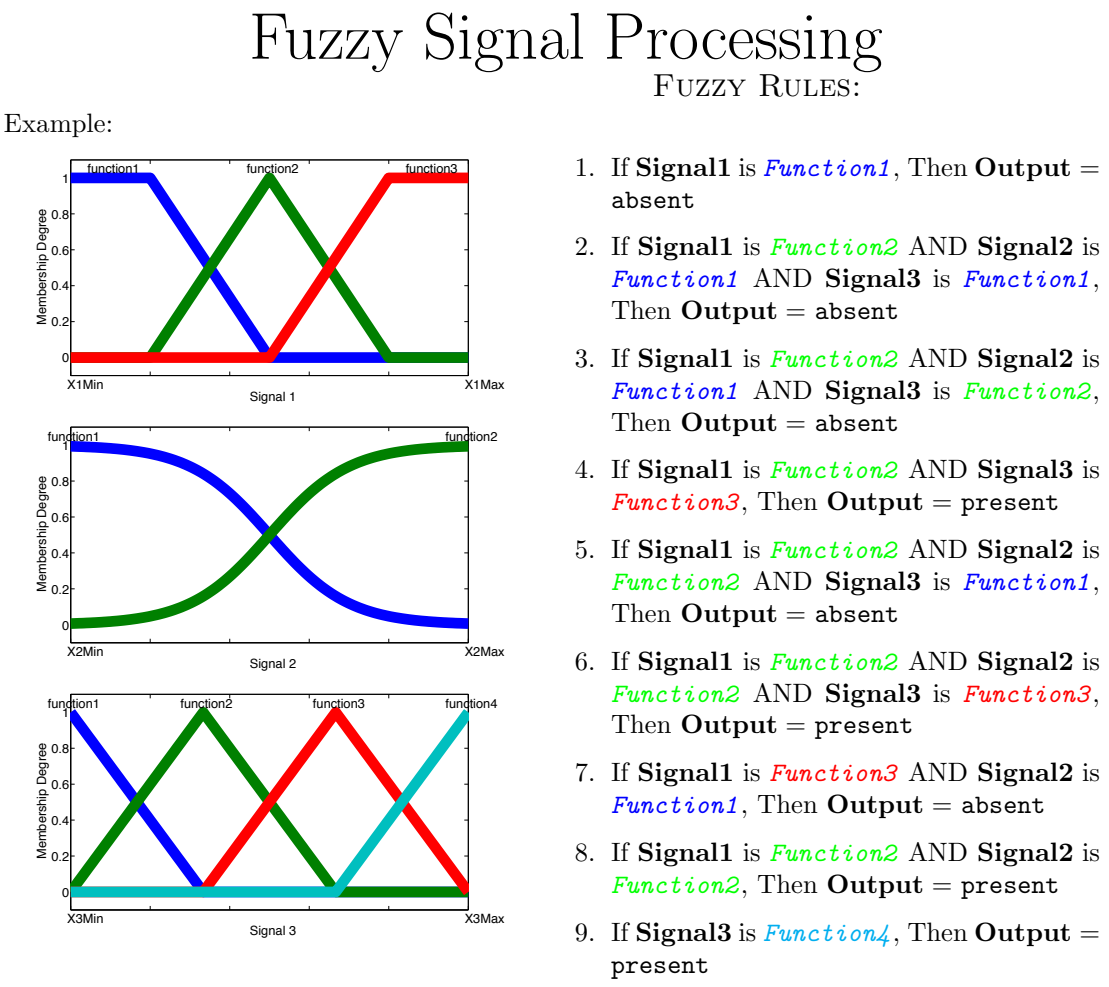


Fig. 5.9: Fuzzy processing example.

This processing model is used in immune-inspired algorithm [de Almeida et al., 2010] for detecting faults in such work, the fuzzy processing is used in the induction of signals with associated rules to four input functions and four output functions, used as numerical information based on mathematical modeling of NK cells production against tumors in [de Pillis et al., 2005], whose variables would be used to generate an alarm index in the method.

The major disadvantage of this modeling is the case of using various inputs and functions related pertinence in which is necessary to include a large number of rules to match these

information.

These methods are considered a part of the process between the treatment of the information generated and the stage of decision making by the immune-inspired algorithm applied to the problem of FDI. There are some other processing forms, however, in this work, only these two forms were used.

5.2.4 New evaluation metrics for DCA

The Dendritic Cell algorithm has two anomaly detection metrics considered in [Greensmith and Aickelin, 2008]: $MCAV$ and K_α, both adopted for antigens and are associated to system contexts, the K_α metric is defined by signals magnitude of exposed cells, proposed to solve difficulties related to biased values of signals (signals of value -1 are treated in the same way that the signal value -100 are treated).

The the $MCAV$ and K_α metrics can be properly exploited for detection or even prevention purposes. However, for the development of an appropriate metric for the FDI applications, both metrics are specific for antigens evaluation and are not suitable in terms of evaluating faults in the dynamic system.

Since the FDI problem is different from anomaly detection problems for which DCA was originally proposed in [Greensmith, 2007], the anomaly metrics applied to the problem should explore the objectives of FDI systems using the outputs of DCA.

In order to achieve the objectives of FDI systems, two additional metrics were proposed in this work. Similar to the other metrics, the outputs of DCA are processed and indexed according to FDI problems.

The Cell Context-Aware Fault Alarm

A new metric, Cell Context-Aware Fault Alarm (CCAFA), is proposed to provide alarms for DCA. This metric consists in the calculation of alarms according to cell responses.

Unlike earlier metrics, the CCAFA is not focused on antigens, instead, this metric relies on the information provided by K, as well as the cell analysis, considering the cell maturation (signal of K).

In $CCAFA$ variable, cells that achieved positive and negative signals of K are evaluated separately and independently of antigens, and then collected in G_K variables, as in (5.13) and (5.14).

$$\sum_{DC} G_K^+ = \frac{\sum_{DC} K^+}{\sum_{DC} M} \tag{5.13}$$

$$\sum_{DC} G_K^- = \frac{\sum_{DC} K^-}{\sum_{DC} Sm} \tag{5.14}$$

To generate normalized and optimized values between -1 and $+1$, the exponential function is employed for both variables, as in (5.15), which turns the metric suitable to detection purposes.

$$\begin{aligned} f(\phi) &= 1 - e^{-\phi} \\ CCAFA &= f(G_K^+) - f(G_K^-) \end{aligned} \tag{5.15}$$

The alarm condition is given by $CCAFA > Alarm_{thr}$, whose value is usually greater than 0 to avoid false alarms. The objective of this metric is to provide a proper fault alarm in the DCA, since most metrics may provide imperfect detection features.

Once presented a detection alarm, an isolation feature will be also presented.

The Antigen Index of Fault Differentiation

Another metric is proposed in this work, The Antigen Index of Fault Differentiation (AIFD) is employed to perform fault isolation in the Dendritic Cell Algorithm. Unlike the CCAFA, this metric is a database oriented index which relies in the antigen correlation and is related to the magnitude of K.

As first implementations of DCA in [Greensmith et al., 2005] were designed to be applied to computer data-based anomaly detection problems, antigens were designed as an identifier of processes, with few influences in signals processing of DCA. Instead, the antigens are influenced by these signals.

In AIS applied to FDI problems, antigens are analogous to the output data of a dynamic system and signals correspond to the behavioral model or some expert system that lead to indicative of faults. In this approach, each antigen can also be evaluated by content, after the evaluation of signals within the cell.

However, at first, the main evaluation consists on identify such differences by DCA variables. Antigens may be defined by their collection by DCs and their association to the exposed signals. The other proposed metric, Antigen Index of Fault Differentiation, aims to collect all antigens

by their quantitative features in the analysis. The index is calculated in (5.16). With $J(a, M)$ being the Jaccard Coefficient of antigens collected by mature cells. The value of K is useful as antigens collected with different magnitude are grouped differently.

$$AIFD(a) = \begin{cases} J(a, M) * \sum(K(a)), & Alarm = 1 \\ 0, & Otherwise \end{cases} \tag{5.16}$$

After antigen indexing through DCA variables, all non-zero values are grouped through this indexes, then, each index is compared to the others by using Euclidean Distance. If the distance does not match any set of stored indexes in the database, a new pattern is stored in database and a new profile is assigned to the detected fault.

Fault profile construction

Once defined both metrics, a fault profile based on antigens is defined through their evaluation. Antigen data will compose rules for fault diagnosis. These rules will be applied for each antigen collected during signal evaluation and fault databases are updated with these information.

As the algorithm performs this task in a deterministic way and each fault has a pattern of antigen collection, each fault point collected through non-zero $AIFD$ variables is attached to a fault profile, even if this antigen is a normal pattern collected during abnormal behavior. The entire scheme is illustrated in Figure 5.10.

It is expected that DCA may achieve satisfactory performance for fault detection and a reasonable results for fault diagnosis based on this strategy.

5.3 Validation of novel metrics

In order to validate the DCA proposed metrics, some tests were performed on the simulations of DC Motor Benchmark. In the experiments analyzed, actuators faults are considered and appropriate signals for detection (the residuals) generated from a linear observer based on the physics of the process.

To provide these simulations, data were collected with observation time $T_o = 1ms$. Each point is collected by their features and all test samples were simulated by $T_s = 4s$. A training sample of $T_s = 1s$ was also collected.

Safe signals are represented as described in Section 5.2.1 for Danger model-based algorithms, and danger signals of DCA are also defined similarly. The algorithm parameters are defined in

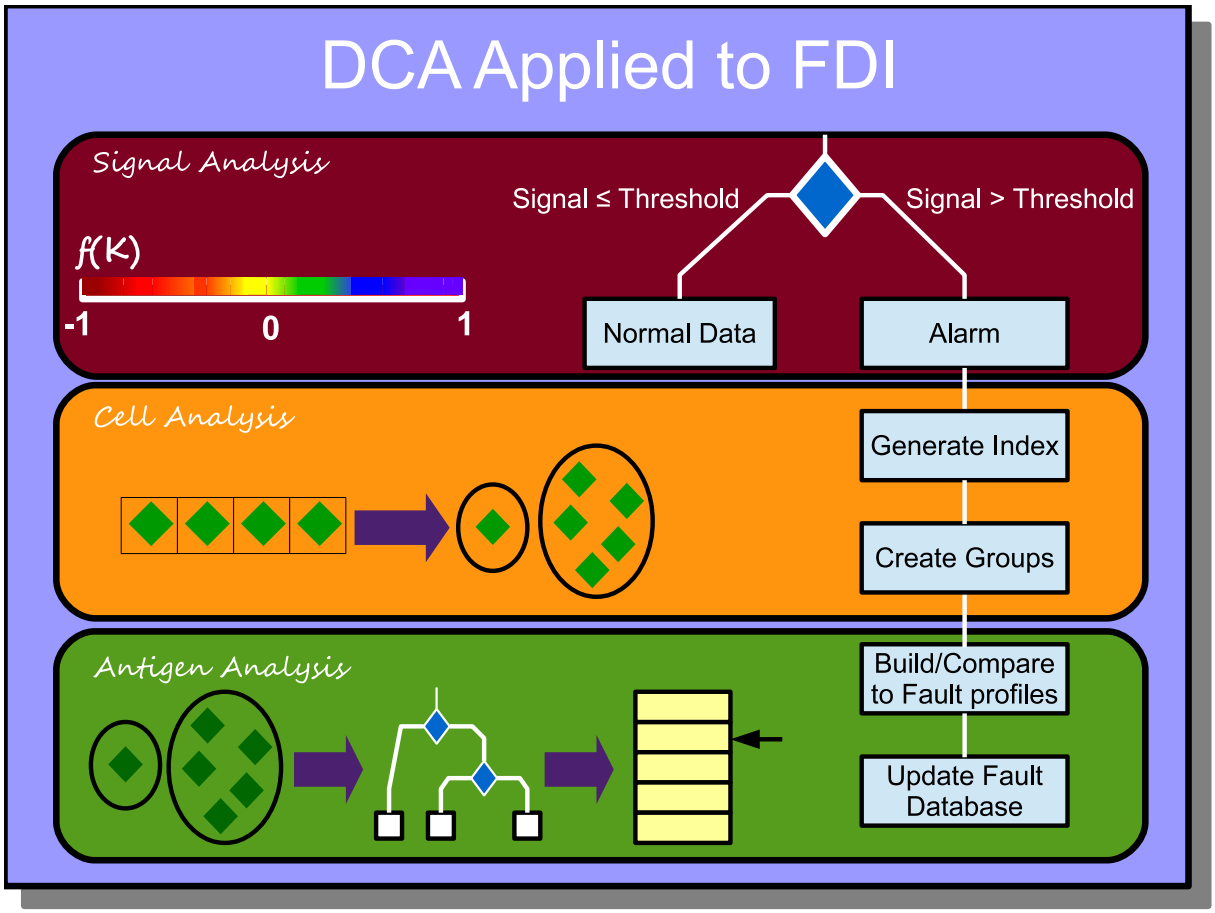


Fig. 5.10: Complete steps of fault diagnosis applied after DCA detection in this work.

Table 5.2. These parameters were defined based on the problem complexity and according to other works in literature.

Deterministic DCA results are presented in Table 5.3, with information about gathered data and the most relevant variables, such as K_α and the proposed metric $CCAFA$, each test has been performed using 4000 points, corresponding to $1ms$ of observed data.

These results point that antigen collection features, which is an important feature of DCA, may not provide the collection of all antigens, related to the exposed signals, by the algorithm agents. Instead, these cells can collect antigens that were exposed to these once during the sampling. However, the fault starts by one second after tests have started. All data processed are represented in figs. 5.11 to 5.14 for Normal Data and figs. 5.15 to 5.30 for Faulty Data.

Tab. 5.2: DCA parameters and functions.

Algorithm Data	
Algorithm Version	`dDCA-FDI`, adapted from `dDCA` [Greensmith and Aickelin, 2008].
DC population	50
Antigen Storage	10
Average Lifetime	5
PAMP	ND
Safe Signal (SS)	Based on Eq. 5.11
Danger Signal (DS)	Based on Eq. 5.10
Min / Max SS	[0 5]
Min / Max DS	[0 10]
Sampling Time (T_s)	$1s$
Evaluation Metrics	$MCAV$, K_α and $CCAFA$

Tab. 5.3: Test results for DCA applied to Fault Detection.

Test Scenario	Detection Instant	Antigens Collected	K_α Max value	K_α Mean value	$CCAFA$ Mean value
Normal	-	-	0	-29.8	-0.60
Fault 1	1s	3	200	+8.69	+0.51
Fault 2	1s	1	200	-0.27	+0.35
Fault 3	1s	40	190	+2.6	+0.49
Fault 4	1s	200	13	-0.32	+0.11

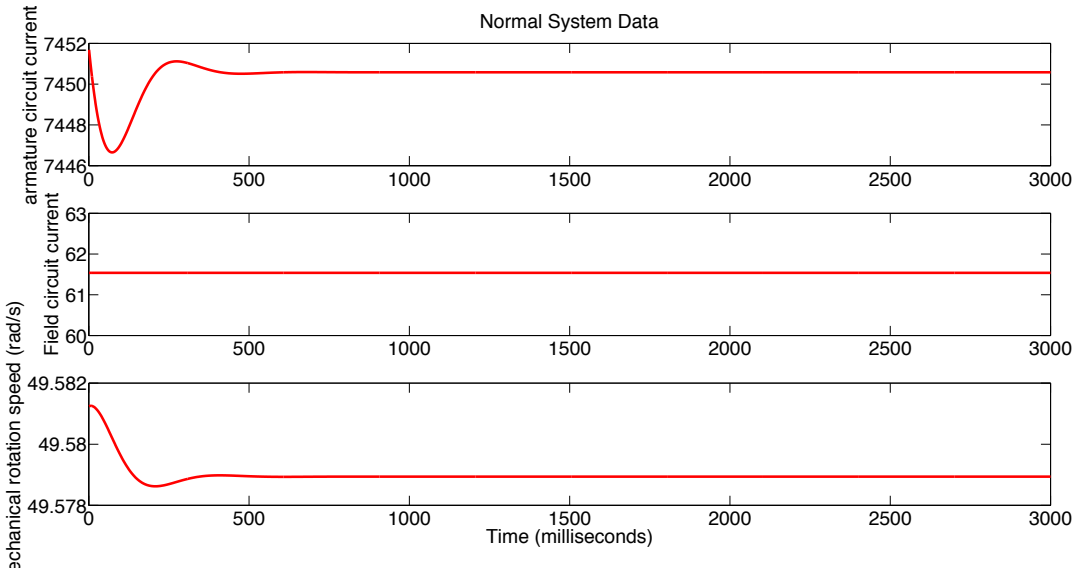


Fig. 5.11: DC Motor system data for Normal Case.

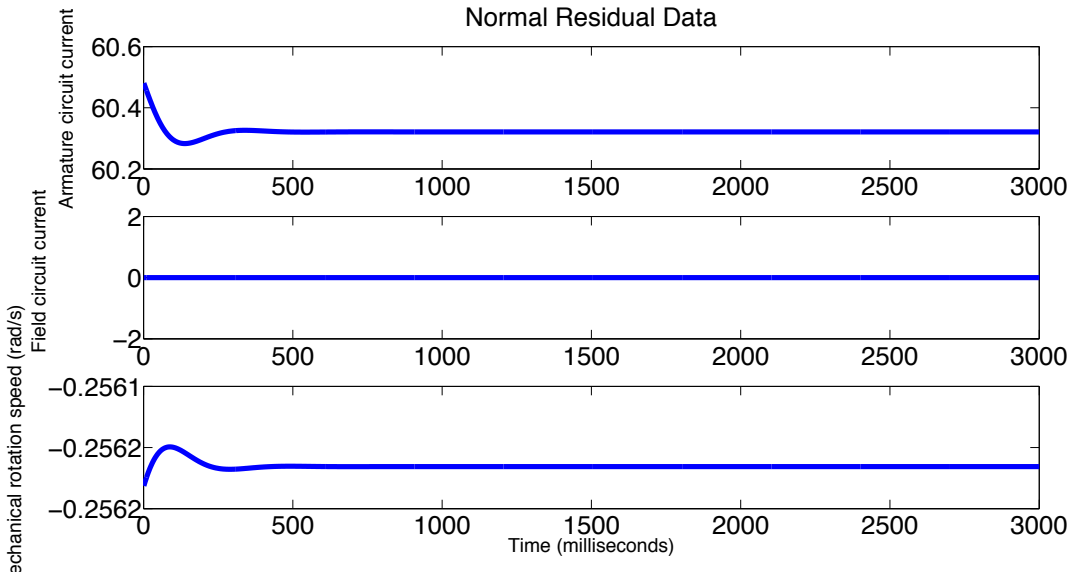


Fig. 5.12: DC Motor residuals data for Normal Case.

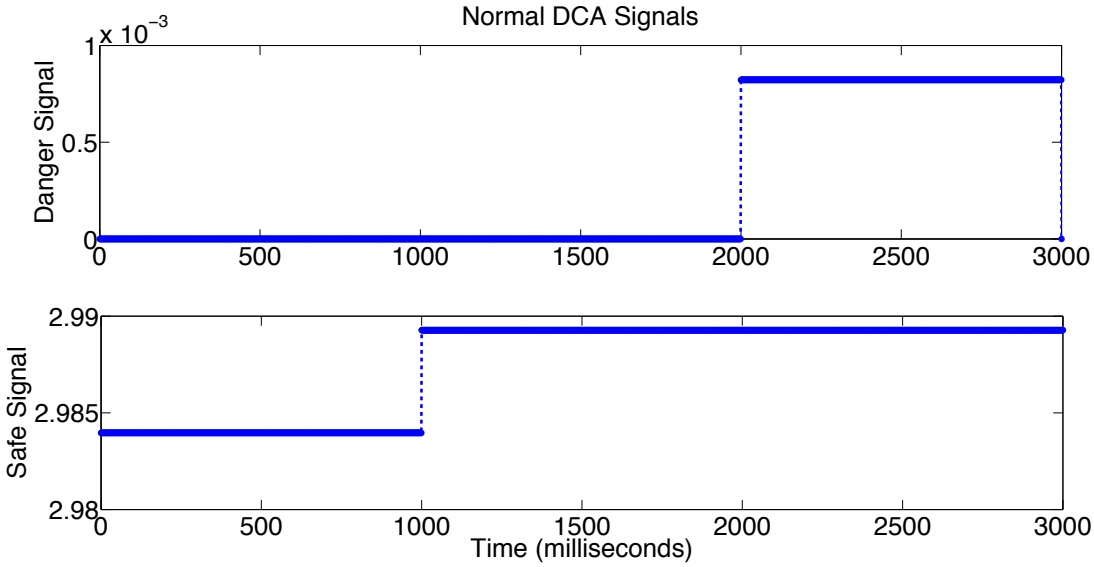


Fig. 5.13: DC Motor converted signals for Normal Case.

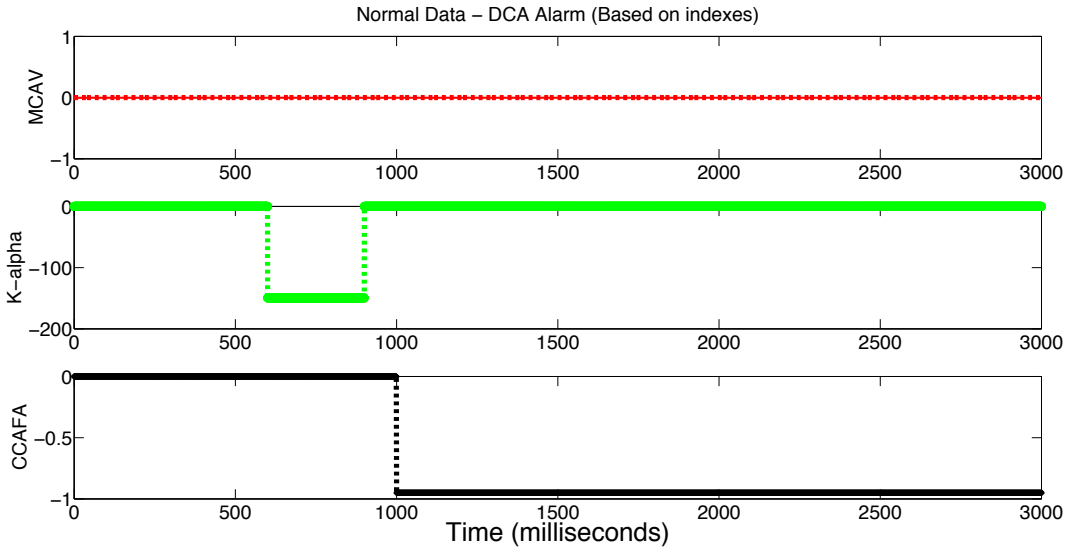


Fig. 5.14: DC Motor alarm data for Normal Case.

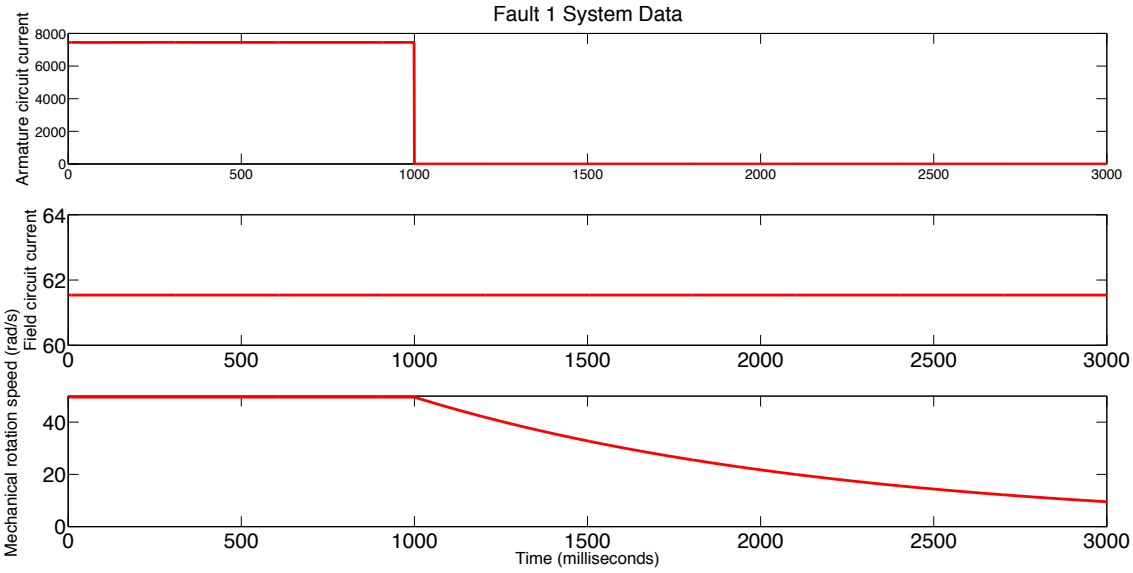


Fig. 5.15: DC Motor system data for Fault 1.

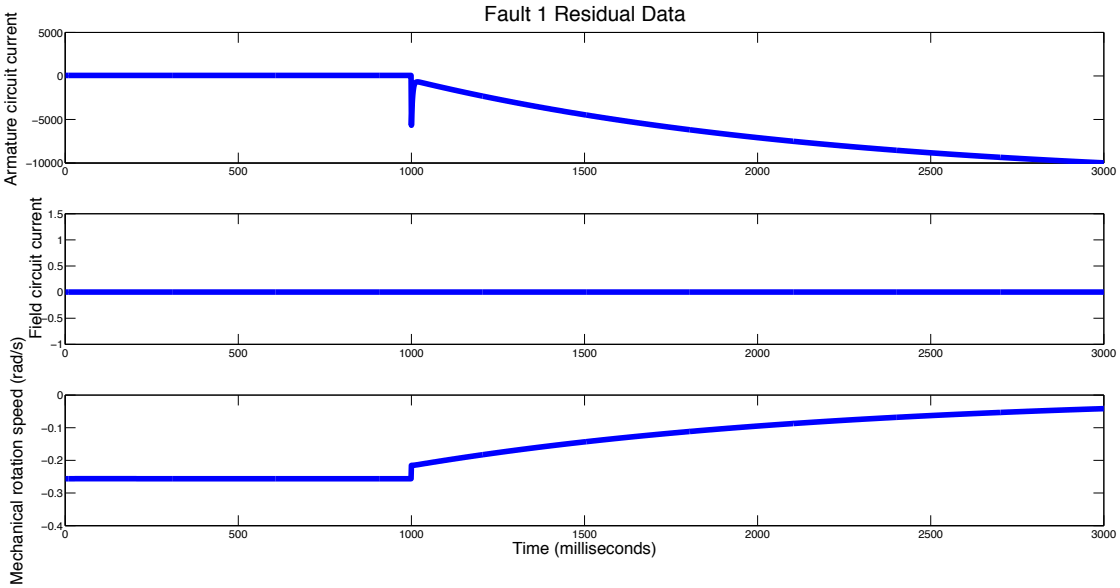


Fig. 5.16: DC Motor residuals data for Fault 1.

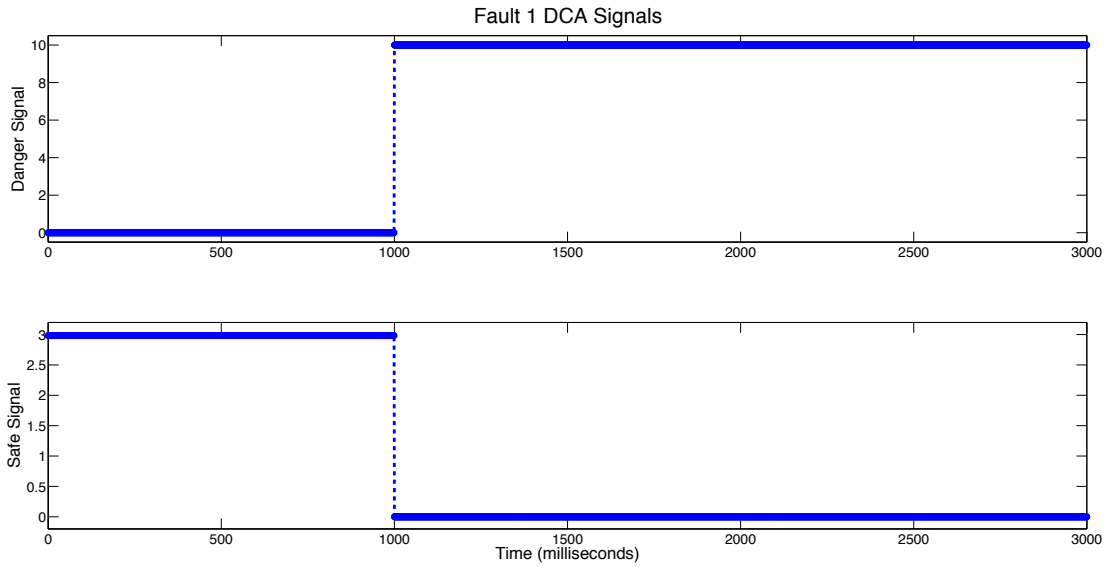


Fig. 5.17: DC Motor converted signals for Fault 1.

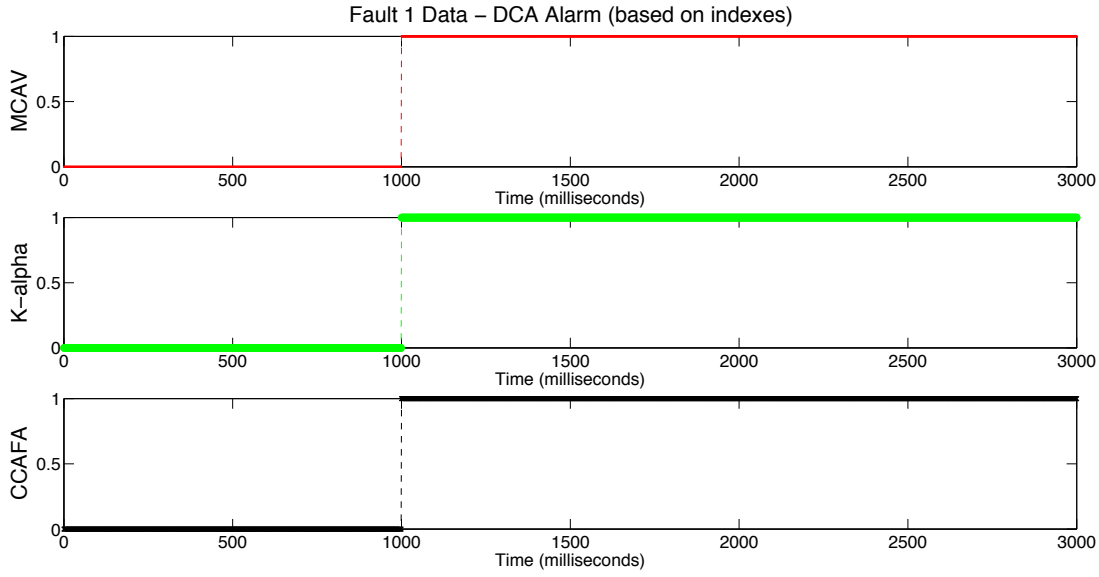


Fig. 5.18: DC Motor alarm data for Fault 1.

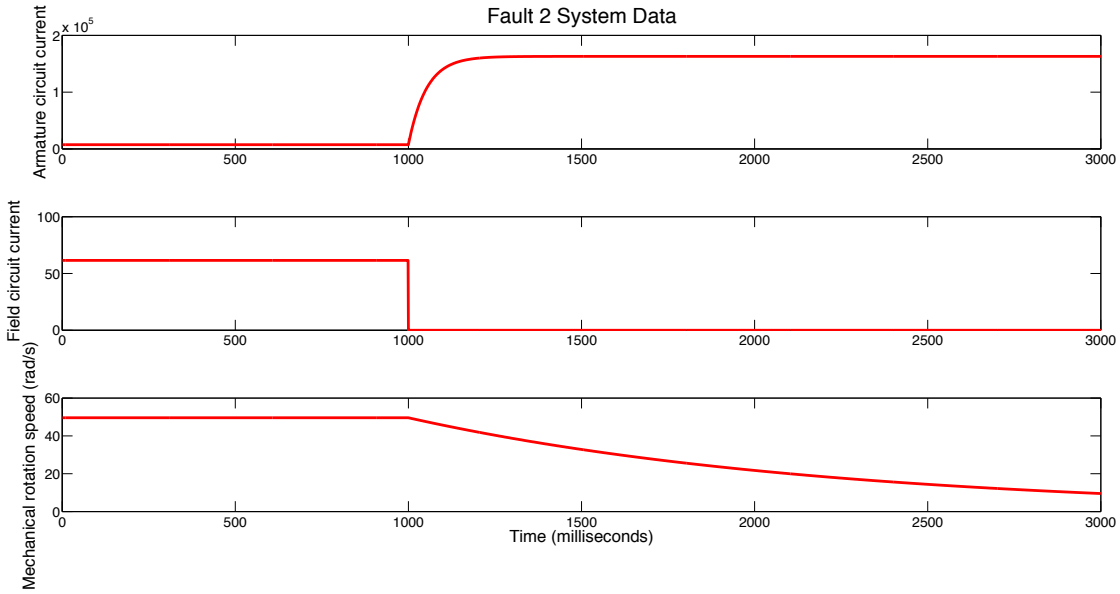


Fig. 5.19: DC Motor system data for Fault 2.

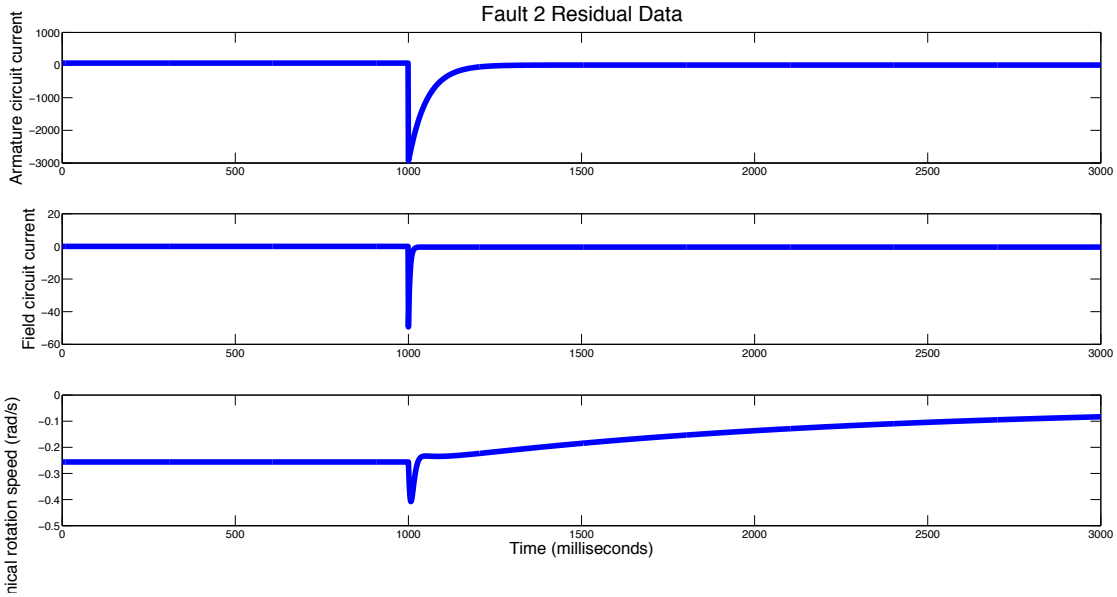


Fig. 5.20: DC Motor residuals data for Fault 2.

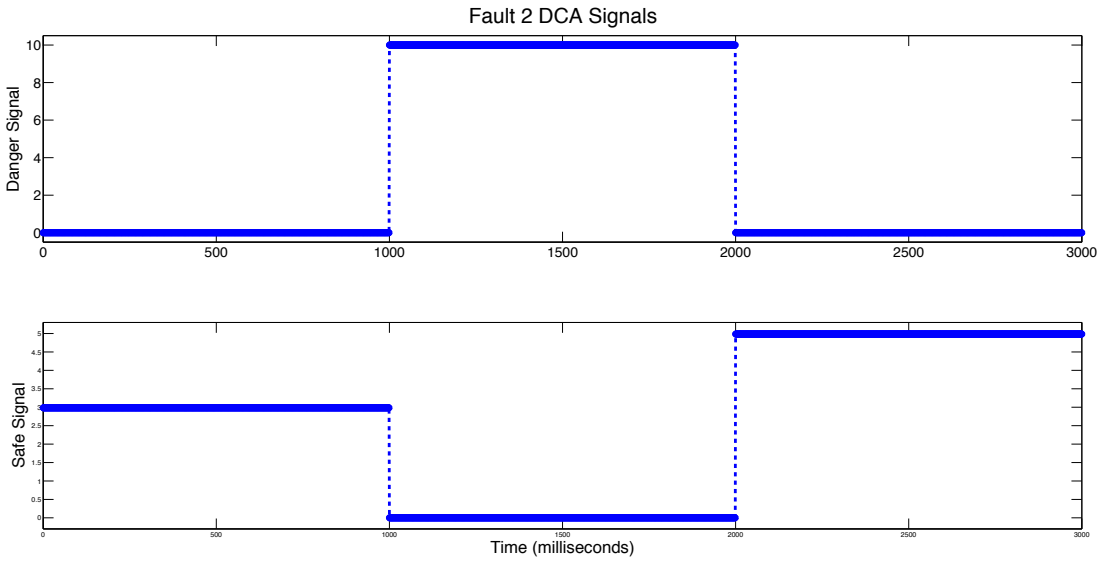


Fig. 5.21: DC Motor converted signals for Fault 2.

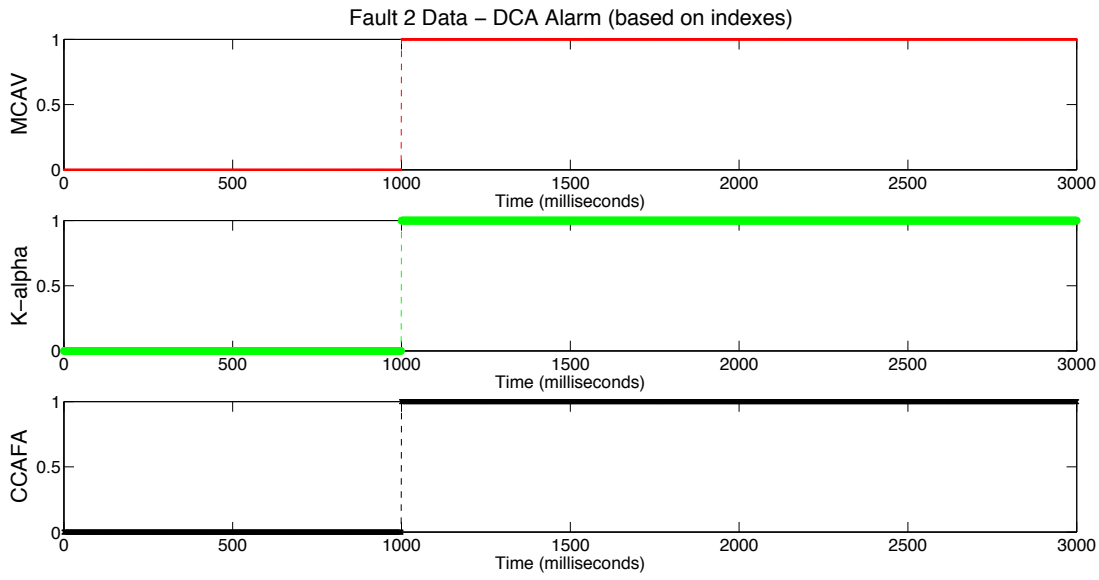


Fig. 5.22: DC Motor alarm data for Fault 2.

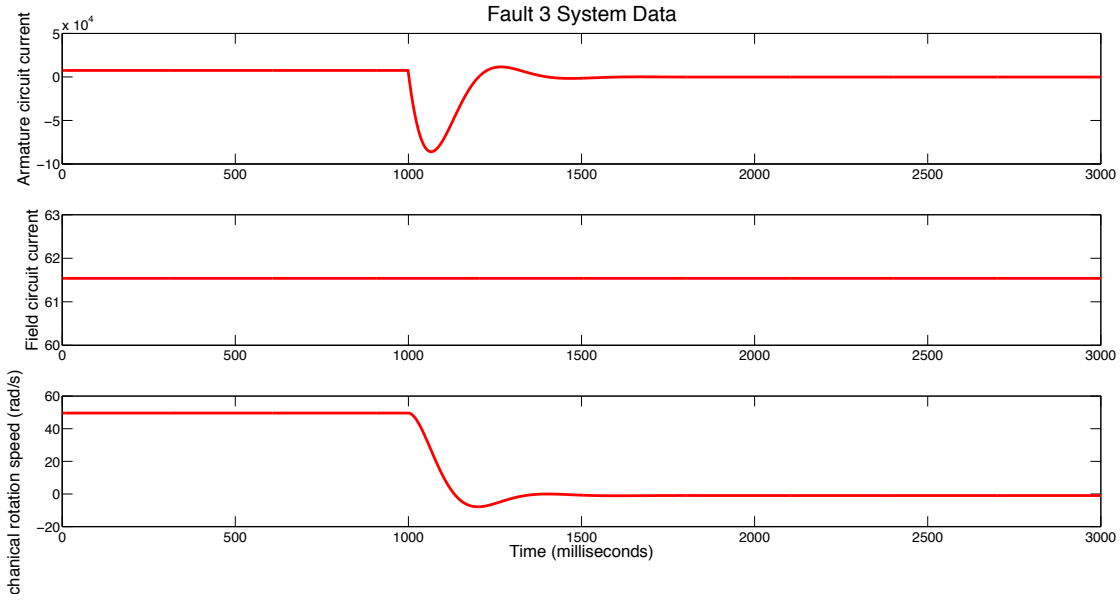


Fig. 5.23: DC Motor system data for Fault 3.

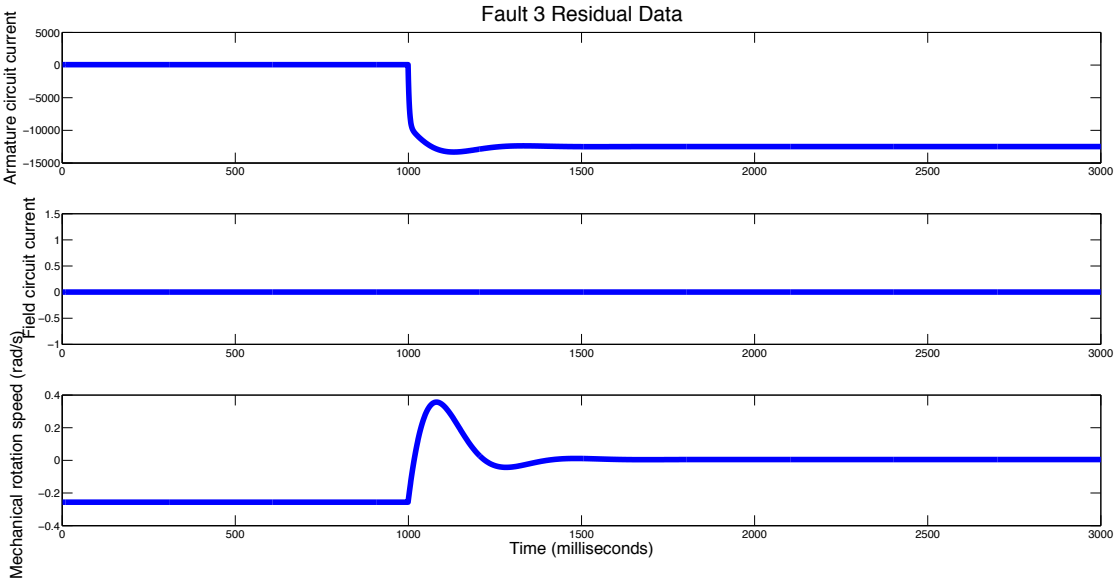


Fig. 5.24: DC Motor residuals data for Fault 3.

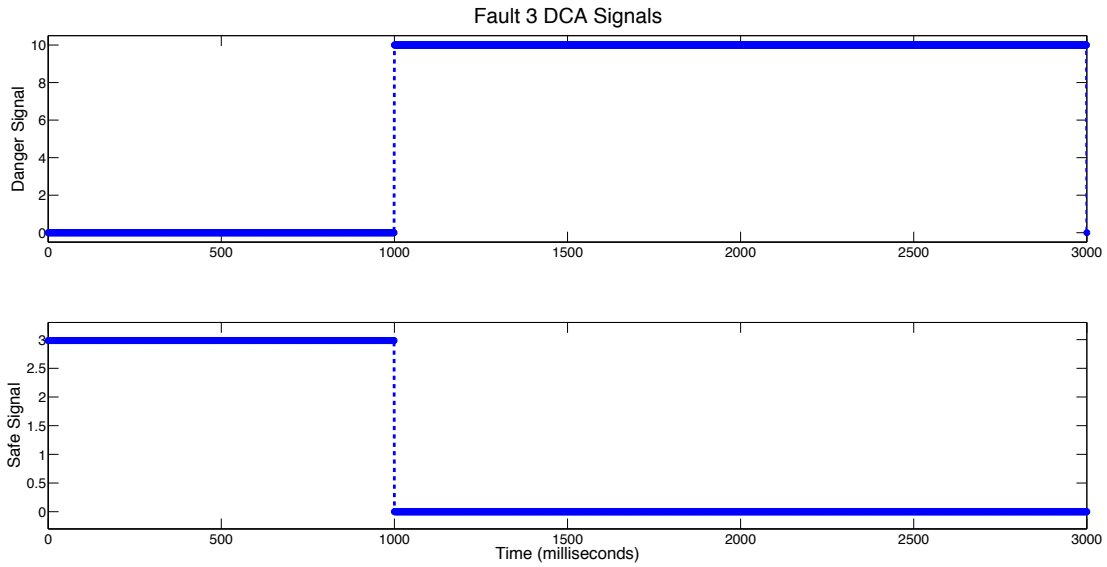


Fig. 5.25: DC Motor converted signals for Fault 3.

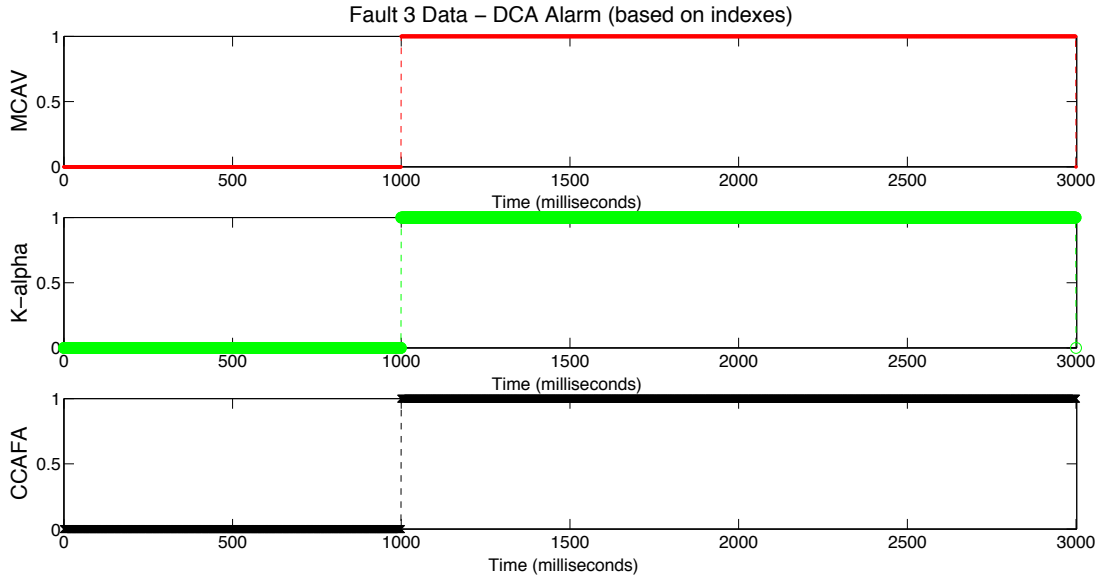


Fig. 5.26: DC Motor alarm data for Fault 3.

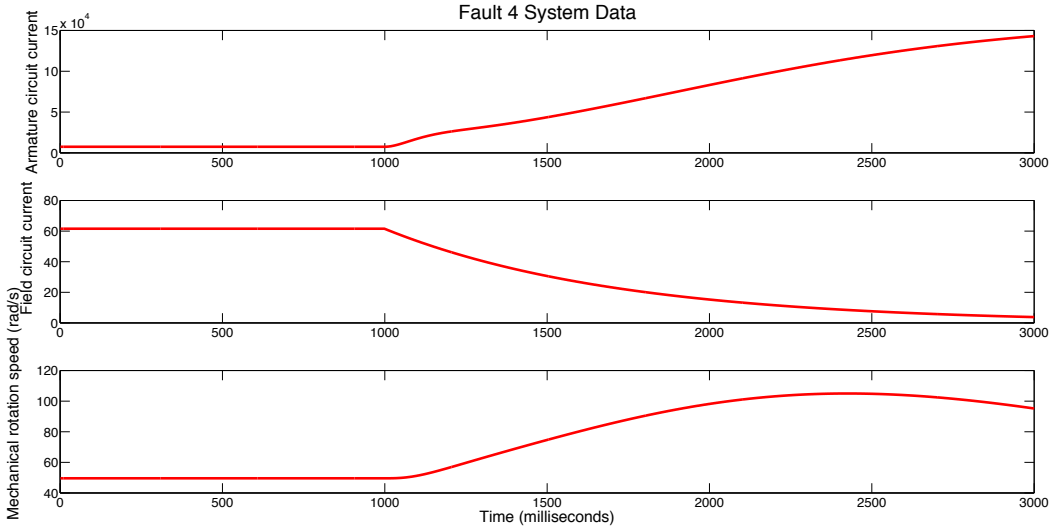


Fig. 5.27: DC Motor system data for Fault 4.

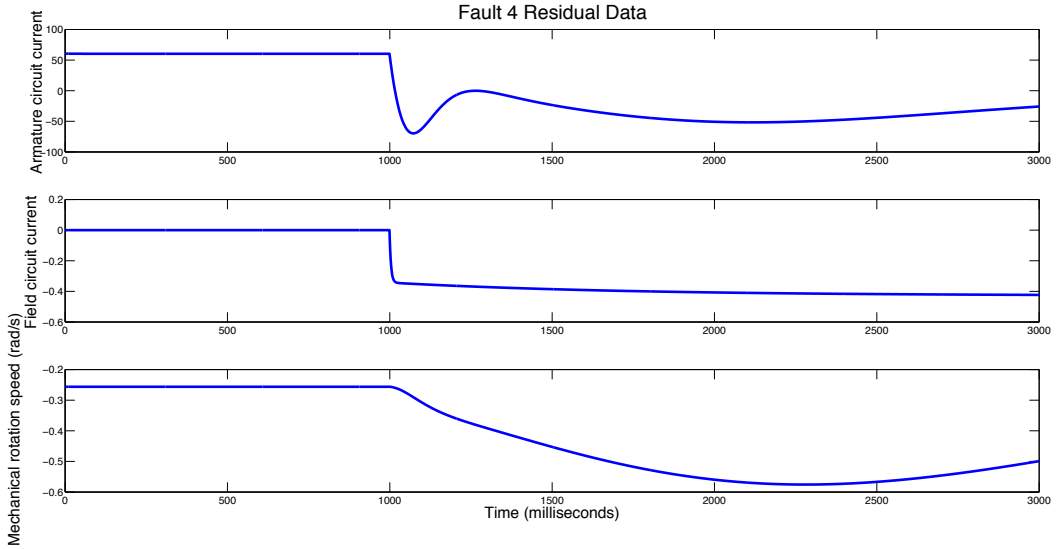


Fig. 5.28: DC Motor residuals data for Fault 4.

Despite the sampling time is different from observed time of the dynamic system, the detection of faults was performed in a relatively accurate time. An interesting data is regarding the mean values of K_α and $CCAFA$ indexes, the latter was proposed to serve as an alarm feature rather than another value to classify antigens, since signals are more relevant to detect faults, which can be shown in Table 5.31. In these data, the $CCAFA$ index seems to be more applicable to detection than K_α, according to their mean values.

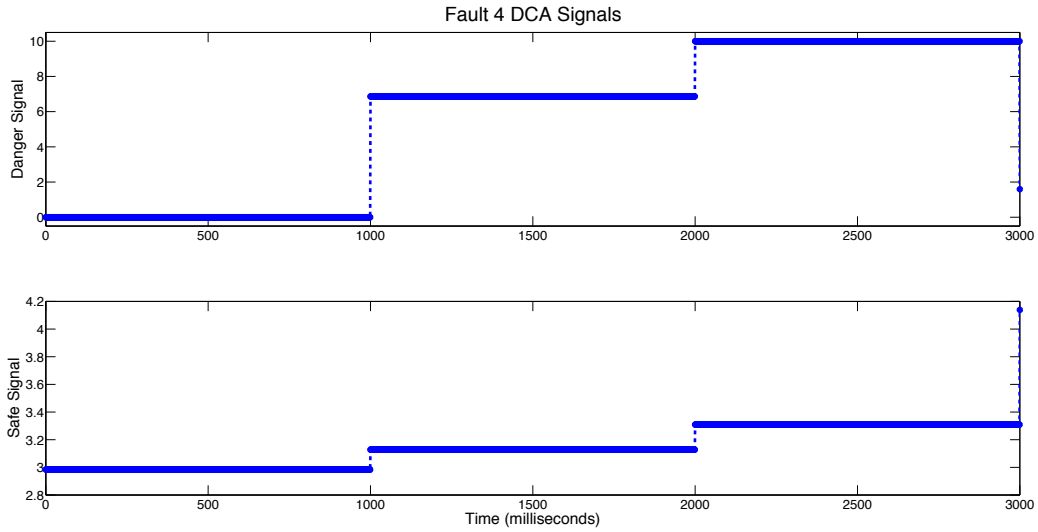


Fig. 5.29: DC Motor converted signals for Fault 4.

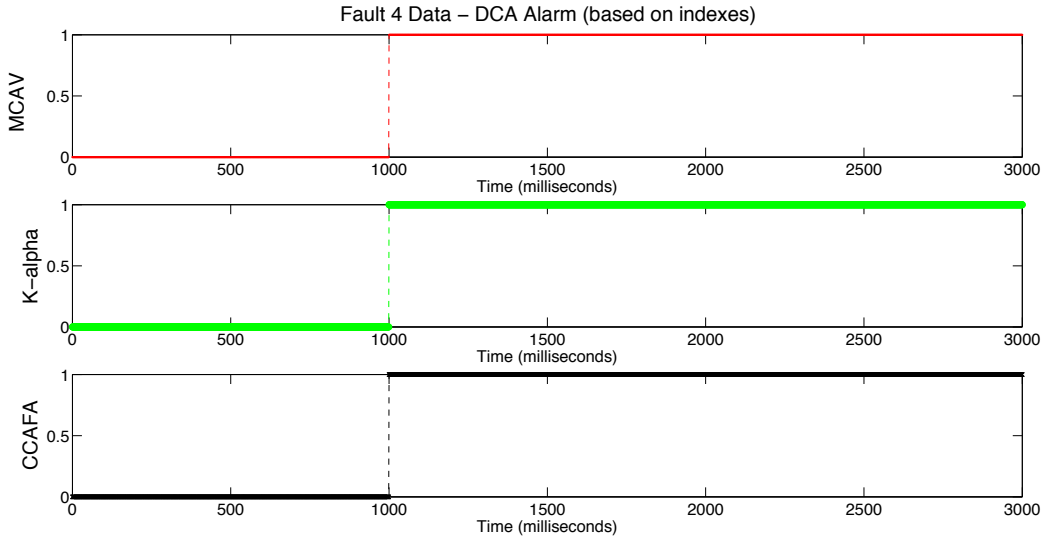


Fig. 5.30: DC Motor alarm data for Fault 4.

However, to verify their suitability for the fault detection problems, a comparison among these indexes may provide such aspects. For this purpose, the detection through each index was measured using a detection threshold as follows.

- $Thr_{MCAV} = 0.6$
- $Thr_{K_\alpha} = 2$
- $Thr_{CCAFA} = 0.2$

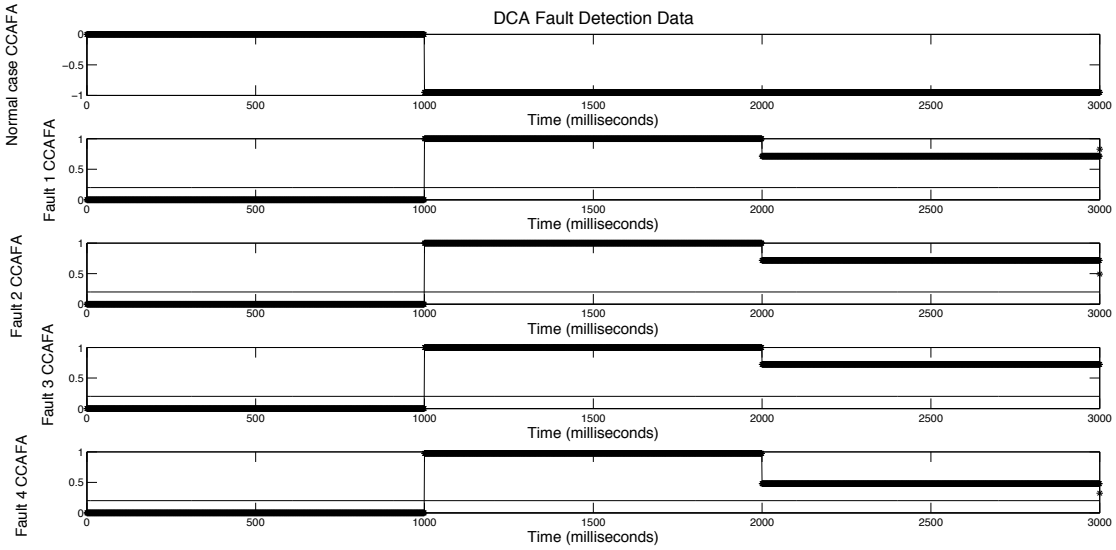


Fig. 5.31: Evaluation of the $CCAFA$ variable with sample time $T_s = 1s$.

The results are given in Table 5.4. Most faults are detectable in such conditions, and the alarm generation is based on these indexes. Unlike in disconnection cases (1 and 2), detection was possible in all instants of detection, short circuit cases (3 and 4) have presented some differences.

Tab. 5.4: Alarm duration time according to anomaly metrics.

Test Scenario	$MCAV$	K_α	$CCAFA$
Normal	0s	0s	0s
Fault 1	3s	3s	3s
Fault 2	3s	3s	3s
Fault 3	2s	2s	3s
Fault 4	3s	3s	3s

These tests point that the new alarm metric proposed in this work is a proper metric for fault detection using DCA functions, since this metric can detect most faults like the other metrics and a comparable performance in most tests as well.

Unlike most anomaly detection cases, FDI problems need some special resources in order to provide identification of different anomaly cases. Most AIS approaches have been often developed to provide well defined detection features. Fault isolation is, however, still limited to other methods.

In the Dendritic Cell Algorithm, an isolation index for antigens, the $AIFD$ was proposed

in Subsection 5.2.4 as an aggregation factor that identifies the fault sequence in the algorithm.

In Table 5.5, some information about the indexes found and antigen patterns are presented with the number of collected antigens with these indexes and when these antigens were collected during DCA evaluation.

Tab. 5.5: Results of antigen indexation through the proposed $AIFD$ index.

Test Scenario	$AIFD$ Indexes	Antigens Evaluated	No. of Antigens	Order of Occurrences
Normal	-	0	11	-
Fault 1	67.20 38.82 2.69	2 2 1	98	3, 98 55-56 54
Fault 2	250	1	552	3
Fault 3	100.81 0.65 0.16	1 12 13	808	3 Both between 629 and 652
Fault 4	7.59 0.07	1 26	2010	3 636-660

This index can also generate distinct sequences of antigen patterns based on the DCA correlation mechanism, as in some cases, consecutive antigens has the same value of $AIFD$ index. Noteworthy, this index is only applicable to the deterministic version of DCA, since the index is a pattern generator that can be reproduced under the same circumstances, according to antigen data.

5.4 Simulations

In this sections, the algorithms reviewed analyzed will be tested, applied to some fault detection benchmarks aiming is to achieve faults as effective as possible. The methods used are the following:

- The Deterministic Dendritic Cell Algorithm (dDCA-FDI).
- Structural Toll-Like Receptors Algorithm (STLR).
- Danger Model-based approach of [de Almeida et al., 2010] (DM-FD).

These tests are proposed to verify and validate all of immune-inspired approaches studied in this work based on performance and how the problem is addressed in each of the employed

methods. These are not explicitly compared to each other, although the performance of each approach is analyzed.

One of the common benchmarks of application in FDI problems is the DAMADICS, introduced in [Bartys et al., 2006] and described in Chapter 2.

There are some methods to generate a redundancy model of the given system, as in [Kourd et al., 2011, Kourd et al., 2013], in which two neural networks are employed to generate the model X' and F' for the residuals of the two outputs, obtained for fault-free and faulty cases. The fault-free case is illustrated in Figure 5.32, whose variables are often evaluated to detect and isolate faults.

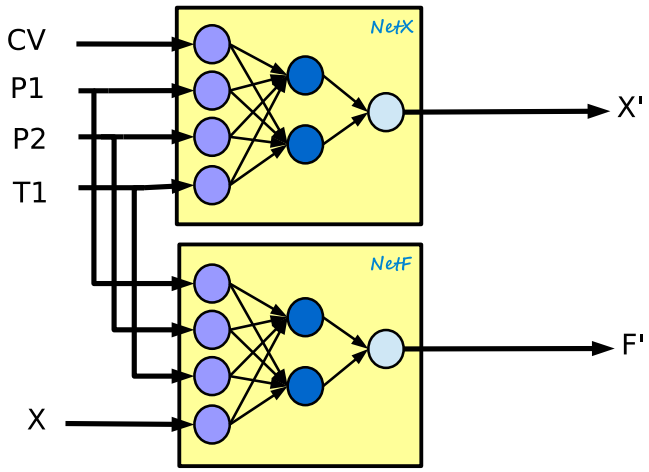


Fig. 5.32: Neural Network for residuals calculation in fault-free simulations of DAMADICS, based in [Kourd et al., 2011].

In those works, detection is based on threshold and residuals evaluation. Some faults can be detected through these strategies, which compare residuals to some sets of range values.

Tests are organized as shown in Table 5.6, with some information as the faults simulated and their strength in the benchmark.

Tab. 5.6: Description of tests performed in DAMADICS benchmark.

Fault Intensity/Type				
ID	Type of fault			
	Abrupt (Intensity)			Inc
	ASm	AMe	ALa	
f0	-	-	-	-
f1	X	X	X	-
f7	X	X	X	-
f13	X	X	X	X
f15	N/A	N/A	X	-
f17	N/A	N/A	X	X
f19	X	X	X	-

Caption for fault types	
None	No Fault
ASm	Abrupt, Small
AMe	Abrupt, Medium
ALa	Abrupt, Large
Inc	Incipient

Residual calculation is provided through the MSE (Mean Square Error) of the estimated and obtained values in all N output variables (Eq. 5.17). For the DCA detection, the calculation of SS is based on a sliding window mechanism, defined by the w value, defined by the period k of the evaluation.

$$r_{(k)} = \frac{\sum_{i=1}^{N}(y_{(k,i)} - \hat{y}_{(k,i)})^2}{N} \tag{5.17}$$

$$SS_{(k)} = \frac{\sum_{j=j_o}^{k} r(j)}{k - j_o} \tag{5.18}$$

$$j_o = max(1, k - w) \tag{5.19}$$

This is the information provided for signals of the evaluated methods. In DCA, the Safe Signal is based on Eq. 5.18, considering the sliding window mechanism calculated upon Eq. 5.19, as the benchmark samples are provided in $T_s = 1s$. Noteworthy, initial value of safe signal is the residual at first instant (i.e. $SS_{(0)} = r_{(0)}$). In this approach, tests are performed in Samples are given in different observed periods, $T_o = \{2, 10, 30, 60, 120\} secs$. And each window, proportional to the period ($w = \frac{T_o}{T_s}$) is evaluated once.

DS calculation is based on the distance between minimum and maximum values of the sliding window, based on (5.20).

$$DS_{(k)} = \sum_{i=1}^{N}(max(r_{(k)}, w) - min(r_{(k)}, w)) \tag{5.20}$$

Normalization equations are defined in Eq. 5.21 for DS and Eq. 5.22 for SS, defining that danger signals have values within range $[0, 10]$ and safe signals have values within range $[0, 5]$.

$$DS'_{(k)} = min(0, max(100DS_{(k)}, 10)) \tag{5.21}$$

$$SS'_{(k)} = max(0, min(1 - 10SS_{(k)}, 1)) * 5 \tag{5.22}$$

Finally, both proposed indexes $CCAFA$ and $AIFD$ are used in these tests as well, in order to provide detection and isolation of faults in this context.

For the TLR algorithm, the antigen is sampled through the sliding window mechanism, instead of the signals, whose processing are still based on the residuals (Eq. 5.17). The sliding window of antigens have the following variation of values $W = \{1, 5, 10, 20\}$, according to the processing, based on the signals. Noteworthy, processing starts from the first instant after the sliding window. (i.e. if $W = 10$, $k_o = 10$ as well), sliding window is also used during the training, as required by processing. As the antigen size is $a_N = 2$, with the sliding window, antigen size becomes $a_N = 2 * W$.

The FD-DM method uses only signal information, which is the same as previous algorithms, and training data (from TLR) will be used during pre-processing. Signals are based on SS used for DCA with normalization considered in 5.23 for $rmax = 80std(SS_{tr})$. The Immune Alarm Threshold ITA is based on the `stressed` fuzzy membership.

$$\bar{Signal}(t) = \begin{cases} 1, & SS_{ts}(t) > rmax \\ \frac{SS_{ts}(t) - rmin}{rmax - rmin}, & \text{Otherwise} \end{cases} \tag{5.23}$$

For these tests, DCA parameters are defined in Table 5.7, TLR algorithm parameters in Table 5.8 and DF-DM Model in Table 5.9, based on this study.

Each scenario is simulated 120 times, and each simulation is considered as an event in which the first detection alarm or maximum time reached are the stopping criteria of the evaluated algorithms. These simulations have random duration (among 4, 8, 16 and 24 hours), and random instant of fault occurrence. Performance measurements, such as detection rate (**dr%**), false alarm rate (**fa%**), and the average detection delay time ($\bar{\Delta}t$) are displayed for each scenario.

Tab. 5.7: DCA parameters and functions.

Algorithm Data	
Algorithm Version	`dDCA-FDI`
APC population	25
Antigen Storage	10
Average DC Lifetime	10
PAMP	ND
Safe Signal (SS)	Based on Eq. 5.18
Danger Signal (DS)	Based on Eq. 5.20
Min / Max SS	[0 5]
Min / Max DS	[0 10]
Sampling Time (T_s)	$2, 30, 60$ or 120 seconds.
Evaluation Metrics	$CCAFA$

Tab. 5.8: TLR parameters and functions.

Algorithm Data	
Algorithm Version	`STLR`
APC Population	20
Average Lifetime	5
Anomaly Detection Algorithms (T-Cell)	`Fuzzy-NSA` or `oc-SVM`
Signals	Residuals-based rules
Processing	Direct, based on Nonself signals.
Sampling Time (T_s)	$1s$
Antigen Sliding Window	$1, 5$ or 10

5.4.1 More about the algorithms

Some points that can be highlighted are using a detector of anomalies that corresponds to the action of T-Cell in TLR Algorithm, whose version used in this work corresponds to the structured version (STLR), and being used with two choices of anomaly detectors, the method of fuzzy antigen recognition proposed in the previous chapter, or a machine learning technique: One-Class SVM proposed in [Schölkopf et al., 2001]. Moreover, two models presented for information processing are adopted: for TLR, the direct processing, based on the original formulation of the algorithm, and the fuzzy processing for the Danger-based approach. And for the Dendritic Cell algorithm, the proposed anomaly detection metrics ($CCAFA$ and $AIFD$, the latter in a further analysis), are considered in this work for evaluation purposes.

The approach in [de Almeida et al., 2010] has few parameters required, and most operations

Tab. 5.9: Method of [de Almeida et al., 2010] parameters and functions.

Algorithm Data	
Algorithm	`DM-FD`
Safe Signal	Based on Eq. 5.11
Min / Max SS	[0 1]
Processing	Fuzzy with 4 inputs and 4 outputs.
Input rules	Based on Costimulatory Signals or Cytokines
Output rules	Based on tumor modeling in [de Pillis et al., 2005].

in the method are based on fuzzy inference analogous to costimulatory signal. The system output was normalized considering the maximum value obtained using training data.

Once defined the three algorithms and their applications, the work will evaluate each algorithm and discuss their obtained performance. The original purpose of these tests is to evaluate the detection capability of the algorithms.

5.4.2 Results

The Benchmark DAMADICS has several points which require a deep analysis of each fault and how to detect them. Each algorithm, as shown throughout this work, has different aspects in which fault detection is performed and the analysis of the benchmark implies analyzing the detection in these different perspectives. Results will be shown in terms of accuracy, detection rate and false alarms.

Deterministic DCA

Deterministic DCA results are presented in Table 5.10 in which sampling is performed in different periods, as shown in the test presentation.

Performance measurements are provided by the Benchmark, whose detection is provided by the $CCAFA$ index. The alarm threshold is $CCAFA \geq 0.05$ for all cases.

Tab. 5.10: Test results for DCA applied to Fault Detection.

Test (ID)	**Scenario**	**Conditions**	**dr%**	**fa%**	$\bar{\Delta}t(TS)$
`f0`	No fault	$TS = 120$	-	0%	-
		$TS = 60$	-	0%	-
		$TS = 30$	-	0%	-
		$TS = 2$	-	0%	-
`f1`	ASm	$TS = 120$	99.17%	0%	2.37
		$TS = 60$	99.17%	0%	2.43
		$TS = 30$	99.17%	0%	2.82
		$TS = 2$	99.17%	0%	2.43
	AMe	$TS = 120$	100%	0%	2.32
		$TS = 60$	100%	0%	2.48
		$TS = 30$	100%	0%	3.02
		$TS = 2$	100%	0%	2.48
	ALa	$TS = 120$	100%	0%	2.11
		$TS = 60$	100%	0%	2.27
		$TS = 30$	100%	0%	2.80
		$TS = 2$	100%	0%	2.27
`f7`	ASm	$TS = 120$	100%	0%	1.54
		$TS = 60$	100%	0%	1.55
		$TS = 30$	100%	0%	1.54
		$TS = 2$	100%	0%	1.55
	AMe	$TS = 120$	100%	0%	1.49
		$TS = 60$	100%	0%	1.52
		$TS = 30$	100%	0%	1.52
		$TS = 2$	100%	0%	1.52
	ALa	$TS = 120$	100%	0%	1.54
		$TS = 60$	100%	0%	1.54
		$TS = 30$	100%	0%	1.57
		$TS = 2$	100%	0%	1.54
	ASm	$TS = 120$	99.17%	0%	1.74

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Tab. 5.10 – continued from previous page

Test (ID)	Scenario	Conditions	dr%	fa%	$\bar{\Delta}t(T_s)$
		$TS = 60$	99.17%	0%	1.87
		$TS = 30$	99.17%	0%	2.14
		$TS = 2$	99.17%	0%	1.87
	AMe	$TS = 120$	100%	0%	1.55
		$TS = 60$	100%	0%	1.63
		$TS = 30$	100%	0%	1.77
		$TS = 2$	100%	0%	1.63
	ALa	$TS = 120$	99.17%	0%	2.34
		$TS = 60$	99.17%	0%	2.45
		$TS = 30$	99.17%	0%	3.23
		$TS = 2$	99.17%	0%	2.45
	Inc	$TS = 120$	100%	0%	2.61
		$TS = 60$	100%	0%	3.39
		$TS = 30$	100%	0%	5.39
		$TS = 2$	100%	0%	3.39
f15	ALa	$TS = 120$	100%	0%	1.88
		$TS = 60$	100%	0%	1.95
		$TS = 30$	100%	0%	2.23
		$TS = 2$	100%	0%	1.95
f17	ALa	$TS = 120$	100%	0%	1.60
		$TS = 60$	100%	0%	1.56
		$TS = 30$	100%	0%	1.56
		$TS = 2$	100%	0%	1.56
	Inc	$TS = 120$	97.5%	0%	10.24
		$TS = 60$	97.5%	0%	19.26
		$TS = 30$	97.5%	0%	39.21
		$TS = 2$	97.5%	0%	19.26
	ASm	$TS = 120$	99.17%	0%	2.91
		$TS = 60$	100%	0%	3.94
		$TS = 30$	100%	0%	6.81

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f19

Tab. 5.10 – continued from previous page					
Test (ID)	**Scenario**	**Conditions**	**dr%**	**fa%**	$\bar{\Delta}t(T_s)$
		$TS = 2$	100%	0%	3.94
	AMe	$TS = 120$	100%	0%	2.1735
		$TS = 60$	100%	0%	2.24
		$TS = 30$	100%	0%	2.689
		$TS = 2$	100%	0%	2.24
	ALa	$TS = 120$	100%	0%	1.81
		$TS = 60$	100%	0%	1.92
		$TS = 30$	100%	0%	2.08
		$TS = 2$	100%	0%	1.92

These results point that DCA may have a good performance when applied to fault detection problems. In most cases, DCA has been successfully applied for most fault cases in DAMADICS Benchmark, even for the incipient faults (`f13` and `f17`), in which the algorithm has detected the fault with minimum delay. For abrupt faults, DCA has achieved good performance mainly in the strong cases.

The algorithm has achieved satisfactory performance for $T_s = 2s$, which is the best sampling time for such experiments, as this sampling time provides the most realistic simulation case. This sampling time has achieved good results considering the detection delay, however, for 10 seconds of sampling, the detection delay was longer than most cases.

All of these tests presented no false alarms, as faulty behavior has not been detected during normal behaviors, indicating that DCA is able to monitor dynamic systems without indicating normal behaviors as faults.

Structural TLR

The other algorithm considered, the Structural version of Toll-like Receptors algorithm has been tested and its results are presented in Tab. 5.11.

Tab. 5.11: Test results for TLR algorithm applied to Fault Detection.

Test (ID)	**Scenario**	**Conditions**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
f0	No fault	$W = 10$ and ocSVM	100%	-	-
		$W = 5$ and ocSVM	100%	-	-
		$W = 1$ and ocSVM	100%	-	-
		$W = 10$ and FuzzyNSA	100%	-	-
		$W = 5$ and FuzzyNSA	100%	-	-
		$W = 1$ and FuzzyNSA	100%	-	-
f1	ASm	$W = 10$ and ocSVM	99.17%	0%	112.93
		$W = 5$ and ocSVM	99.17%	0%	112.95
		$W = 1$ and ocSVM	99.17%	0%	112.97
		$W = 10$ and FuzzyNSA	99.17%	0%	113.04
		$W = 5$ and FuzzyNSA	99.17%	0%	113
		$W = 1$ and FuzzyNSA	99.17%	0%	112.92
	AMe	$W = 10$ and ocSVM	100%	0%	42.96
		$W = 5$ and ocSVM	100%	0%	42.97
		$W = 1$ and ocSVM	100%	0%	42.97

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Tab. 5.11 – continued from previous page

Test (ID)	Scenario	Conditions	dr%	fa%	$\bar{\Delta}t(sec)$
		$W = 10$ and FuzzyNSA	100%	0%	42.90
		$W = 5$ and FuzzyNSA	100%	0%	42.93
		$W = 1$ and FuzzyNSA	100%	0%	42.88
	ALa	$W = 10$ and ocSVM	100%	0%	99.26
		$W = 5$ and ocSVM	100%	0%	99.23
		$W = 1$ and ocSVM	100%	0%	99.28
		$W = 10$ and FuzzyNSA	100%	0%	99.29
		$W = 5$ and FuzzyNSA	100%	0%	99.26
		$W = 1$ and FuzzyNSA	100%	0%	99.34
f7	ASm	$W = 10$ and ocSVM	100%	0%	1.28
		$W = 5$ and ocSVM	100%	0%	1.34
		$W = 1$ and ocSVM	100%	0%	1.30
		$W = 10$ and FuzzyNSA	100%	0%	1.28
		$W = 5$ and FuzzyNSA	100%	0%	1.32
		$W = 1$ and FuzzyNSA	100%	0%	1.33

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Tab. 5.11 – continued from previous page

Test (ID)	Scenario	Conditions	dr%	fa%	$\bar{\Delta}t(sec)$
	AMe	$W = 10$ and `ocSVM`	100%	0%	1.23
		$W = 5$ and `ocSVM`	100%	0%	1.36
		$W = 1$ and `ocSVM`	100%	0%	1.32
		$W = 10$ and `FuzzyNSA`	100%	0%	1.21
		$W = 5$ and `FuzzyNSA`	100%	0%	1.36
		$W = 1$ and `FuzzyNSA`	100%	0%	1.23
	ALa	$W = 10$ and `ocSVM`	100%	0%	1.24
		$W = 5$ and `ocSVM`	100%	0%	1.32
		$W = 1$ and `ocSVM`	100%	0%	1.29
		$W = 10$ and `FuzzyNSA`	100%	0%	1.28
		$W = 5$ and `FuzzyNSA`	100%	0%	1.23
		$W = 1$ and `FuzzyNSA`	100%	0%	1.30
	ASm	$W = 10$ and `ocSVM`	99.17%	0%	24.46
		$W = 5$ and `ocSVM`	99.17%	0%	24.51
		$W = 1$ and `ocSVM`	99.17%	0%	24.39

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Tab. 5.11 – continued from previous page

Test (ID)	Scenario	Conditions	dr%	fa%	$\bar{\Delta}t(sec)$
		$W = 10$ and FuzzyNSA	99.17%	0%	24.42
		$W = 5$ and FuzzyNSA	99.17%	0%	24.47
		$W = 1$ and FuzzyNSA	99.17%	0%	24.44
	AMe	$W = 10$ and ocSVM	100%	0%	12.75
		$W = 5$ and ocSVM	100%	0%	12.78
		$W = 1$ and ocSVM	100%	0%	12.74
		$W = 10$ and FuzzyNSA	100%	0%	12.83
		$W = 5$ and FuzzyNSA	100%	0%	12.70
		$W = 1$ and FuzzyNSA	100%	0%	12.78
	ALa	$W = 10$ and ocSVM	99.17%	0%	44.48
		$W = 5$ and ocSVM	99.17%	0%	44.42
		$W = 1$ and ocSVM	99.17%	0%	44.44
		$W = 10$ and FuzzyNSA	99.17%	0%	44.49
		$W = 5$ and FuzzyNSA	99.17%	0%	44.48
		$W = 1$ and FuzzyNSA	99.17%	0%	44.47

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Tab. 5.11 – continued from previous page

Test (ID)	Scenario	Conditions	dr%	fa%	$\bar{\Delta}t(sec)$
	Inc	$W = 10$ and `ocSVM`	100%	0%	157.87
		$W = 5$ and `ocSVM`	100%	0%	157.85
		$W = 1$ and `ocSVM`	100%	0%	157.89
		$W = 10$ and `FuzzyNSA`	100%	0%	157.88
		$W = 5$ and `FuzzyNSA`	100%	0%	157.92
		$W = 1$ and `FuzzyNSA`	100%	0%	157.87
`f15`	ALa	$W = 10$ and `ocSVM`	100%	0%	20.58
		$W = 5$ and `ocSVM`	100%	0%	20.59
		$W = 1$ and `ocSVM`	100%	0%	20.60
		$W = 10$ and `FuzzyNSA`	100%	0%	20.53
		$W = 5$ and `FuzzyNSA`	100%	0%	20.57
		$W = 1$ and `FuzzyNSA`	100%	0%	20.53
	ALa	$W = 10$ and `ocSVM`	100%	0%	1.26
		$W = 5$ and `ocSVM`	100%	0%	1.31
		$W = 1$ and `ocSVM`	100%	0%	1.27
`f17`					

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Tab. 5.11 – continued from previous page

Test (ID)	Scenario	Conditions	dr%	fa%	$\bar{\Delta}t(sec)$
		$W = 10$ and FuzzyNSA	100%	0%	1.33
		$W = 5$ and FuzzyNSA	100%	0%	1.31
		$W = 1$ and FuzzyNSA	100%	0%	1.26
	Inc	$W = 10$ and ocSVM	97.5%	0%	1608.27
		$W = 5$ and ocSVM	97.5%	0%	1608.15
		$W = 1$ and ocSVM	97.5%	0%	1608.24
		$W = 10$ and FuzzyNSA	97.5%	0%	1608.19
		$W = 5$ and FuzzyNSA	97.5%	0%	1608.28
		$W = 1$ and FuzzyNSA	97.5%	0%	1608.31
f19	ASm	$W = 10$ and ocSVM	0%	0%	-
		$W = 5$ and ocSVM	0%	0%	-
		$W = 1$ and ocSVM	0%	0%	-
		$W = 10$ and FuzzyNSA	0%	0%	-
		$W = 5$ and FuzzyNSA	0%	0%	-
		$W = 1$ and FuzzyNSA	0%	0%	-

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Tab. 5.11 – continued from previous page

Test (ID)	Scenario	Conditions	dr%	fa%	$\bar{\Delta}t(sec)$
	AMe	$W = 10$ and `ocSVM`	96.67%	0%	270.11
		$W = 5$ and `ocSVM`	96.67%	0%	270.10
		$W = 1$ and `ocSVM`	96.67%	0%	270.14
		$W = 10$ and `FuzzyNSA`	96.67%	0%	270.10
		$W = 5$ and `FuzzyNSA`	96.67%	0%	270.14
		$W = 1$ and `FuzzyNSA`	96.67%	0%	270.21
	ALa	$W = 10$ and `ocSVM`	100%	0%	21.06
		$W = 5$ and `ocSVM`	100%	0%	21.04
		$W = 1$ and `ocSVM`	100%	0%	20.99
		$W = 10$ and `FuzzyNSA`	100%	0%	21.01
		$W = 5$ and `FuzzyNSA`	100%	0%	21.09
		$W = 1$ and `FuzzyNSA`	100%	0%	21.16

The TLR algorithm achieved a good performance even for incipient faults without false alarms in any test. However, for `f19`, TLR failed to detect them in the small case. The detection time was relatively satisfactory in some faults, but DCA achieved a better result in most cases.

Using the antigen sliding window mechanism for 10 samples, TLR has achieved a good performance, mainly for incipient faults. however, changing the size of the window, the per-

formance has not increased significantly. TLR can also achieve detection for 1 sample in the sliding window

It was assumed that use of another algorithm to define self and nonself regions should also influence in the performance, however, comparing the One Class SVM method and the Fuzzy version of Negative Selection, TLR has achieved similar performance in both cases.

In counterpart, the mechanism used for detection has prevented the occurrence of false alarms in the algorithm, in a similar way to DCA. Compared to the latter algorithm, TLR had better performance, but still with some false alarms in few cases.

Danger Model inspired fault detection

The danger model approach proposed in [de Almeida et al., 2010] used for simulations is tested for comparisons among all approaches. The Table 5.12 presents the results achieved in the research.

Tab. 5.12: Test results for the danger model approach applied to Fault Detection.

Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
`f0`	No fault	-	0%	-
`f1`	ASm	99.17%	0%	380.46
	AMe	99.17%	0%	432.16
	ALa	95.85%	0%	430.96
`f7`	ASm	99.17%	0%	132.03
	AMe	100%	0%	118.89
	ALa	100%	0%	136.80
`f13`	ASm	96.67%	0%	287.02
	AMe	100%	0%	225.03
	ALa	95.83%	0%	452.85
	Inc	99.17%	0%	365.56
`f15`	ALa	97.50%	0%	351.38
`f17`	ALa	99.17%	0%	139.18
	Inc	99.17%	0%	1297
`f19`	ASm	96.67%	0%	2326
	AMe	95%	0%	820.44

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Tab. 5.12 – continued from previous page				
Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
	ALa	95.85%	0%	464.36

The algorithm was able to detect most faults, but with poor performances, mainly for `f1`, `f15` and `f19` cases. A reasonable performance for incipient faults was achieved, but in some cases, the algorithm had some problems related to the delay in fault detection.

Another algorithm - One-class SVM and PCA

The One-class Support Vector Machine, proposed in [Schölkopf et al., 2001], was chosen in order to provide comparisons to immune-inspired approaches. Once used as nonself space in TLR tests in this work, the method was evaluated taking into account that one-class methods are more suitable approaches for fault detection problems.

The SVM approach was tested with the output pre-processed by PCA considering the strategy performed in [Zhanchun et al., 2006], using gaussian kernel as separation surface, with threshold $\mu = 0.0000028$. Considering the high rate of false alarms of such methods, an alarm tolerance index AT was considered, with $AT = 2$, which means that only the third point of negative class being an alarm. Results for this test are presented in Figure 5.13.

Tab. 5.13: Test results for the SVM one class with PCA applied to Fault Detection.

Test (ID)	**Scenario**	**dr%**	**fa%**	$\bar{\Delta}t(sec)$
f0	No fault	0%	42%	0
f1	ASm	90.83%	9.17%	44.67
	AMe	0%	10.83%	0
	ALa	88.33%	11.67%	37.56
f7	ASm	86.67%	13.33%	2.79
	AMe	86.67%	13.33%	2.89
	ALa	82.5%	17.5%	2.89
f13	ASm	45.83%	15%	12947
	AMe	43.33%	13.33%	14046
	ALa	0%	15%	0
	Inc	87.5%	10.83%	735.4
f15	ALa	86.67%	13.33%	13.68
f17	ALa	89.17%	10.83%	2.97
	Inc	90%	10%	380
f19	ASm	23.33%	13.33%	23389
	AMe	1.67%	13.33%	29916
	ALa	0.83%	13.33%	39102

Compared to AIS approaches, these algorithms had some false alarm rate. In addition, the strategy failed to detect some faults and provided a longer delay in detection, being unfeasible for this application.

Computational Costs and Runtime Complexity analysis

It is known that classical immune-inspired approaches based on the negative selection have high computational costs, as described in [de Almeida et al., 2010]. Regarding the approaches considered in this work, particularly in the case study of DAMADICS, some information has been achieved.

Based on [Gu et al., 2013], the runtime complexity of DCA has been calculated based on theorems. These theorems state that complexity relies on the data size and, in segmented

processing, also relies on the population of APCs and the segment size. The DCA worst case has a quadratic runtime complexity based on the data size. Other algorithms, such as TLR Algorithm, have not been analyzed so far in the literature.

In this work, most of the DCA computational cost is regarding the consequences of its pre-processing phase, in which data are converted to signal and antigen format in order to be analyzed by the algorithm, whose computational cost can be relatively low.

The TLR Algorithm, however, have its computational cost based on the signal rules and antigen data evaluations, implying a possibly high computational cost, depending on the processed data.

The approach proposed in [de Almeida et al., 2010] presents a low computational cost as implied by its data processing, which requires few evaluations compared to the other approaches.

In order to evaluate these aspects, some data regarding the runtime of algorithms applied to DAMADICS were obtained and presented in Table 5.14. These data are presented in terms of execution time.

Tab. 5.14: Runtime execution data of the algorithms evaluated in this study (in seconds).

Algorithm	Min	Max	Mean	Median	Standard Deviation
DCA $T_s = 120$ (Pre-processing)	0.741	38.11	11.37	13.39	11.47
DCA $T_s = 120$ (Algorithm)	0.049	18.78	4.99	4.03	4.21
DCA $T_s = 60$ (Pre-processing)	0.734	41.02	11.37	13.39	11.42
DCA $T_s = 60$ (Algorithm)	0.036	20.36	5.35	4.03	4.56
DCA $T_s = 30$ (Pre-processing)	0.782	38.98	11.69	13.76	11.78
DCA $T_s = 30$ (Algorithm)	0.028	24.03	6.09	4.82	5.32
DCA $T_s = 2$ (Pre-processing)	1.468	53.9	15.76	18.81	14.62
DCA $T_s = 2$ (Algorithm)	0.014	465	92.29	43.08	115
TLR+ocSVM $W = 1$	0.0023	54.06	14.87	11.49	12.52
TLR+ocSVM $W = 5$	0.0019	53.75	14.91	11.53	12.57
TLR+ocSVM $W = 10$	0.0012	53.03	14.75	11.37	12.44
TLR+FuzzyNSA $W = 1$	0.0037	99.91	27.83	21.47	23.44
TLR+FuzzyNSA $W = 5$	0.0036	131.46	36.58	28.18	30.83
TLR+FuzzyNSA $W = 10$	0.0034	170.38	47.40	36.57	39.96
FD-DM	0.014	69.0	17.52	13.71	14.46

Considering these data, most immune-inspired approaches may present some complexity as implied by their mechanisms. For the 2-second sampling case, DCA presented a large runtime complexity, probably because of the cell evaluation. TLR also presents large execution runtimes, considering these results, however, using One-class SVM, the runtime execution can be lower than using the Fuzzy Antigen Recognition. For the Danger Model method, as expected, low

Tab. 5.15: DDR values for antigens collected by DCA in DAMADICS tests.

	f1	f7	f13	f15	f17	f19
f1	0	0.9074	0.7437	1.3932	0.7168	1.8803
f7	0.9074	0	1.2187	1.7834	1.2938	1.3155
f13	0.7437	1.2187	0	1.1213	0.6342	1.0069
f15	1.3932	1.7834	1.1213	0	1.2237	1.1003
f17	0.7168	1.2938	0.6342	1.2237	0	0.7284
f19	1.8803	1.3155	1.0069	1.1003	0.7284	0

runtime execution data was obtained, since this method performs few evaluations in signal data.

DCA Fault Isolation Scheme

The $AIFD$ index generated by DCA has produced 6 to 8 distinct profiles related to a part of the monitored variables of the benchmark. In DAMADICS Benchmark, the isolation considers the antigen related to the monitored output and its gathered values during fault occurrence.

The stimulated variables present $AIFD$ values greater than zero, as these are properly influenced by DCA detection. This stimulation may depend on the fault strength and the type of fault considered. Noteworthy, the minimum threshold of isolation for each antigen is $D < 0.4$, considering the Euclidean Distance between each monitored point.

In order to provide a proper fault isolation, two metrics were adopted, the Distinguishable Distance Ratio (DDR) proposed in [Wang and Liu, 2009], and the Ambiguity Ratio (AR) improved in [Wang and Liu, 2011]. These metrics can be used to provide measurements on class ambiguity in classification problems.

The DDR is a metric based on the Euclidean Distance between two centroids and the standard deviation of both classes, as described in (5.24). This metric consists of measuring the distinction of a class i related to j, values close to zero imply that both classes are similar. In addition, the relation of DDR is symmetric, that is, $DDR_{(i,j)} = DDR_{(j,i)}$.

$$DDR_{(i,j)} = \frac{Dist(c_i, c_j)}{\gamma * (std_i + std_j)} \tag{5.24}$$

Where γ is a given constant considering the number of standard deviations from each centroid.

A matrix of distincion between classes was obtained. This matrix is shown at Table 5.15.

Tab. 5.16: AR values for antigens collected by DCA in DAMADICS tests.

	f1	f7	f13	f15	f17	f19
f1	1	0.0202	0.0909	0	0.0241	0
f7	0	1	0	0.0309	0	0
f13	0	0.0349	1	0.0844	0.1530	0
f15	0	0.0268	0	1	0.0057	0
f17	0	0.0419	0	0.1057	1	0
f19	0	0.0132	0.0909	0	0.0494	1

The AR metric has a different context, consists of an algorithm that provides the ambiguous degree of class j relative to class i. The algorithm equations are available in 5.25 to 5.28.

$$AR(i,j) = \frac{A(i,j)}{A(i,i)} \tag{5.25}$$

$$A(i,j) = \frac{\sum_{q=1}^{n_j} U_i(Xj_q) * P_i(Xj_q)}{n_j} \tag{5.26}$$

$$U_i(Xj_q) = \begin{cases} 1, & Dist(Xj_q, c_i) \leq Dist(Xj_q, c_j) \\ 0, & Dist(Xj_q, c_i) > Dist(Xj_q, c_j) \end{cases} \tag{5.27}$$

$$P_i(Xj_q) = \begin{cases} 0, & Dmax_i < Dist(Xj_q, c_i) \\ \sqrt{\frac{Dmax_i - Dist(Xj_q, c_i)}{Dmax_i}}, & Dmin_i \leq Dist(Xj_q, c_i) \leq Dmax_i \\ 1, & Dist(Xj_q, c_i) < Dmin_i \end{cases} \tag{5.28}$$

Where $Dmin$ and $Dmax$ are the minimum and the maximum of Euclidean Distances from all instances in i to the centroid c_i, respectively, for all n_i values of class i.

In AR, values close to one indicate a high ambiguity degree between two classes, while values close to zero indicate that both classes are not ambiguous. Different from DDR, the relation of $AR(i,j)$ is not symmetric, that is, $AR(i,j) \neq AR(j,i)$.

The ambiguity matrix between isolated faults is shown at Table 5.16.

According to both matrices, faults could be isolated properly, with high degrees of distinction and low degrees of ambiguity. Some cases, such as distinction relations between `f13` and `f17` for example, may indicate possibilities of the fault being isolated wrongly. Noteworthy, faults like `f1` and `f19` are difficult to isolate, as $AIFD$ values were critically low at most tests for these faults.

These results point that the $AIFD$ index is applicable, and most faults in these tests are

possible to isolate. However, isolation can be harder than in other benchmark studies and it can occur under certain circumstances.

Discussion

The main point in common about these approaches is the false alarm rate, which is nonexistent for all approaches tested in this work. Considering the performance in DAMADICS tests and the use of certain threshold values, these approaches have different ways to deal with processing, mainly in the decision phase.

Dendritic Cell and Toll-Like Receptor algorithms have achieved good performance in these tests. DCA has provided a persistent detection, as well as a satisfactory isolation mechanism, and the TLR algorithm has provided two signals for detection: residuals (PAMP) and a different pattern (Antigen). Both algorithms have detected most faults in DAMADICS case study.

The other Danger Model inspired approach has achieved reasonable, but worse results considering the delay in fault detection. Since the processing is totally different from the other algorithms, the delay in detection may represent an issue in this algorithm.

These algorithms are capable to provide a low rate of false alarms. But since the expert knowledge is very important for the application, the discussion regarding the application of these approaches as FDI systems may be conditioned to the use of models. For all purposes, Danger Model inspired approaches, mainly the DCA, may provide some interesting resources for detection in these cases.

Chapter 6

Concluding Remarks

This chapter presents the overall conclusion of the work, as well as subjects for future researches that are yet to be explored in AIS studies.

6.1 Main aspects of the research

In this work, several studies were consolidated, such as the study of immunological models and which features they can offer to provide some enhanced techniques for fault detection and, in some cases, fault isolation.

Initially, an immune-inspired anomaly detector based on fuzzy antigen recognition of T cells was presented in two forms: one of them verifies if a detector to be allocated is in a feasible region (nonself) in order to detect anomalies; the other form detects anomalies based on the distance between of training and validation points.

Both algorithms are based on the two phases of negative selection, each of them corresponding to an algorithm, both approaches uses information of distance and fuzzy inference system to achieve the anomaly detection.

Although the algorithms based on negative selection has inherent flaws on context or applications, it is possible to make them applicable in certain cases, especially in learning machine problems, moreover, the addition of other immune mechanisms algorithms can be considered.

Infectious Nonself and Danger Models based algorithms have an expert knowledge required to model the signals, which usually is not implicit in the databases. However, this feature may be extended to statistical or qualitative aspects.

The main issue about using Dendritic Cell Algorithm in the FDI problems is the antigen correlation mechanism, which performs a pattern building rather than collecting the faulty points during signal evaluation through cells. This function has been exploited in this work

and adds a question in the research: how good the exploitation of the antigen correlation mechanism in FDI problems should be.

The Toll-Like Receptor Algorithm has a scheme similar to DCA representation, inspired in the Infectious nonself model and innate immunity. This algorithm requires a minimum experts knowledge, and also has a training mechanism which defines signals and conditions of activation. The algorithm in [Twycross et al., 2010] was based on data from censorship, both for signals as to the antigens. Receptors may, however, be based on processing rules, consideration taken in this work, which makes it simpler to define if these signals are infectious.

In fact, many dynamic systems have few operational information, it becomes the indication of possible anomalies a challenging task. It is assumed that traditional approaches can also be applied, based on the supervised training mechanism, which can also be adopted for modeling experts knowledge database. This study studies also confirmed some idea about these algorithms: There is no better immune inspired model than another, thus, some features of each model can be integrated in some approaches, allowing possible extensions in the AIS theory.

Overall, the present work has offered some alternatives to improve the reviewed AIS approaches and apply them to fault detection problems in order to provide satisfactory and encouraging results with good detection rates and no false alarm rates, showing that the alternate immune response models can represent a good metaphor for fault detection.

6.2 Further works

The modeling of immune inspired systems has been significantly enhanced with the study of the transitional link between the approaches, allowing some analogies to be employed as follows.

For the fuzzy antigen recognition algorithm, other immune-inspired fuzzy rules may be exploited in some future works, some of them related to other immunological models, which may be used to define the valid conditions for negative selection rules, and others such as anergy, exploited in [Cayzer and Sullivan, 2007], when the system may not respond to anomalous conditions in some cases. In addition, the mechanism can also be applied to evaluation of training performance in machine learning algorithms, as the negative selection may provide a good strategy in order to avoid over-fitting in these approaches.

It is noteworthy that the model is incomplete and may require other mechanisms to improve their operation. However, the results show that it is possible to apply the algorithm approaches relatively simple, with some applicability in the literature, since the fuzzy recognition immune system may be an attractive alternative in terms of systems engineering.

The fuzzy antigen recognition algorithm still has features that should be analyzed, such as

implementation of other fuzzy rules inspired by immunological mechanisms and the thresholds generation for fault detection, as well as the mechanism of death by neglect in monitoring, which may play a role that is still unknown.

In DCA, there are still many other factors to be considered in addition to the expert knowledge required to assess the problem. Among them study of the parameters and the challenge of finding an optimal combination of parameters. In this deterministic version, considered in the work, there are few parameters required for adjustments. Since biological inspiration may offer other analogies, there are some other ways to improve such algorithms and gather better results for anomaly detection problems. Another aspect that can be studied is the applicability of DCA to fault prognosis problems, as the signal analysis can be used to assess the remaining useful life of a system.

However, TLR and FD-DM approaches have not a potential mechanism for fault isolation as the antigen correlation for DCA, for this purpose, these algorithms may have to suffer some changes to allow fault isolation and identification tasks. Some other aspects yet to be studied are alternatives to redundancy models in order to serve as expert model for these approaches.

Since the transitional links among immunological models have been studied, these aspects can be combined in order to offer an evolving model for AIS approaches based on each feature provided by these models, then developing an alternate immune inspired system able to evolve and optimize its structure to improve detection and isolation capabilities.

Another feature of the biological immune system that studies should deepen is the biological signaling feature. Some AIS have immune signaling features, but these features are treated basically. Since immune signaling rules the biological immune system in order to provide changes, the study of signaling features and their application to engineering problems can be an interesting study and may enrich the analysis.

The cognitive paradigm of immune system also have interesting features that can enrich AIS approaches and provide an interesting inspiration for novel approaches. There are few studies in this paradigm and its analysis can also improve some existing approaches significantly. A combination of these features (evolving, signal-focused and cognition) may provide interesting models for novel AIS approaches.

Most approaches, however, are designed for centralized dynamical systems. For large distributed systems, the application of these methods would be a complicated task. Such systems require the employment of methods that evaluate data hierarchically and these method also must be distributed to deal with system complexity. Most AIS approaches are centralized and they may not work on distributed environments. Deal with large distributed systems is quite challenging and novel approaches should be developed in order to solve these problems.

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