UNIVERSIDADE DE LISBOA
FACULDADE DE CIÊNCIAS

A dependability framework for WSN-based aquatic monitoring systems

" Documento Definitivo"

Doutoramento em Informática

Especialidade de Engenharia Informática

Gonçalo João Vitorino de Jesus

Tese orientada por:

Prof. Doutor António Casimiro

Doutora Anabela Oliveira

Documento especialmente elaborado para a obtenção do grau de doutor

2019

UNIVERSIDADE DE LISBOA
FACULDADE DE CIÊNCIAS

A dependability framework for WSN-based aquatic monitoring systems

Doutoramento em Informática

Especialidade de Engenharia Informática

Gonçalo João Vitorino de Jesus

Tese orientada por:

Prof. Doutor António Casimiro

Doutora Anabela Oliveira

Júri:
Presidente:

- Doutor Nuno Fuentecilla Maia Ferreira Neves, Professor Catedrático, Faculdade de Ciências da Universidade de Lisboa

Vogais:

- Doutor Marco Paulo Amorim Vieira, Professor Catedrático, Faculdade de Ciências e Tecnologia da Universidade de Coimbra
- Doutor Luís Miguel Pinho de Almeida, Professor Associado, Faculdade de Engenharia da Universidade do Porto
- Doutor André Bustorff Fortunato, Investigador Principal com Habilitação, Departamento de Hidráulica e Ambiente do Laboratório Nacional de Engenharia Civil (LNEC)
- Doutor Luís Miguel Parreira e Correia, Professor Associado com Agregação, Faculdade de Ciências da Universidade de Lisboa
- Doutor António Casimiro Ferreira da Costa, Professor Associado, Faculdade de Ciências da Universidade de Lisboa (Orientador)
- Doutor Pedro Miguel Frazão Fernandes Ferreira, Professor Auxiliar, Faculdade de Ciências da Universidade de Lisboa

Documento especialmente elaborado para a obtenção do grau de doutor

Laboratório Nacional de Engenharia Civil
Fundação para a Ciência e Tecnologia - SFRH/BD/82489/2011

2019

Acknowledgements

Este estudo que realizei foi uma experiência que exigiu bastante de mim ao longo dos últimos anos e não teria sido possível sem a ajuda, directa e indirecta, das seguintes pessoas e instituições a quem quero agradecer o apoio, acompanhamento e ajuda.

À Doutora Anabela Pacheco de Oliveira, co-orientadora e chefe de núcleo no LNEC, agradeço o apoio incondicional, a amizade e a possibilidade de levar a cabo a investigação a nível aplicado que este estudo exigiu.

Ao Professor António Casimiro, orientador científico da tese, agradeço a supervisão e ajuda prestada. O meu sincero agradecimento pelas opiniões críticas e partilha de conhecimento, bem como a disponibilidade para a correcção dos vários artigos e relatórios.

Agradeço o apoio financeiro do Laboratório Nacional de Engenharia Civil e da Fundação para a Ciência e Tecnologia, através da bolsa de doutoramento. À FCT, em particular pelo financiamento da bolsa SFRH/BD/82489/2011. Ao LNEC, muito além da bolsa de doutoramento, a oportunidade, os projectos e os recursos que disponibilizaram e que permitiram a realização deste estudo.

Agradeço também à Fundação Luso-Americana para o Desenvolvimento pelo financiamento de viagens de cooperação ao Center for Coastal Margin Observation & Prediction (CMOP). E ao CMOP, especialmente ao Professor António Melo Baptista pela sua generosidade, simpatia, motivação, e que me acolheu e disponibilizou todos os meios para que pudesse estudar e aplicar as contribuição deste trabalho. Ainda um agradecimento ao Paul Turner pela disponibilidade em partilhar o seu conhecimento.

Um obrigado a todos os meus colegas do núcleo de Tecnologias de Informação, sem esquecer os que seguiram o seu caminho para outras áreas. À Doutora Maria Alzira, ex-chefe do núcleo, pelas suas palavras amigas e apoio que sempre demonstrou. Ao Nuno, Palha Fernandes, Américo e Ana, pela grande amizade e partilha de conhecimento. Agradeço ainda a companhia amiga dos meus colegas informáticos, João Gomes e Jonez por confiarem em mim, por me desafiarem tecnicamente e pelas muitas discussões construtivas que tivemos.

A todos os colegas com os quais pude privar de perto nos projectos em que trabalhámos, em especial, ao Alberto, Marta, André, Manuel, Paula e Armando, pela partilha de experiências.

Aos meus amigos João, Sílvia e Adelaide, por me fazerem sentir em casa, no LNEC, desde o momento em que vos conheci em 2007. Um grande obrigado pela vossa amizade que muito prezo.

A todos os meus amigos de Alcobaça, Cape Town, Coimbra e Lisboa, Ana Teresa, André Amador, André Correia, Andrew, Ângelo, Catarina, Cristina, Dani, Drop, Fernandos, Filipe, Filipa, Henrique, Hugo, Kai, Joel, Juneid, Malhão, Maria, Maria Joana, Óscar (sempre desaparecido), Pedro (vários), Penas, Sam, Ricardo, Rodrigo, Ruben, Teles, Vanessa, ..., pelo vosso companheirismo, amizade e paciência. Um obrigado também por todos os planos sociais que tivemos e que serão repetidos no futuro, dos quais destaco as viagens, idas à neve, surf, jogos de futebol ou as muitas frutíferas conversas infindáveis.

Agradeço também a todos os colegas do LNEC que me enchem o coração cada vez que entro nesta instituição. Obrigado pelo acolhimento e toda a força que fizeram para que eu realizasse este estudo.

À Tia Graciete, Tio Alberto, Padrinho Vítor e Madrinha Deolinda, agradeço o vosso carinho e peço desculpa pela minha ausência, que espero poder corrigir de futuro. Peço ainda desculpa às minhas primas Marina, Beatriz e Alicia, por ter sido complicado estar presente nas vossas vidas nos últimos anos.

Aos meus pais, um agradecimento eterno. é impossível descrever e retribuir o vosso apoio incondicional e a disponibilidade imensa que tiveram sempre para comigo. Este último ano foi ainda mais atípico, invadi o vosso espaço (e obrigado Tia Graciete pela cedência do escritório) após tantos anos fora, e a Mãe e o Pai acolheram-me e fizeram tudo para que eu pudesse focar-me apenas na conclusão deste estudo.

Para finalizar, gostaria de dedicar este trabalho à memória da minha avó Celeste e do meu avô Maca, duas das pessoas mais importantes da minha vida, que acompanharam as minhas escolhas e que infelizmente não podem celebrar comigo agora.

Abstract

Wireless Sensor Networks (WSN) are being progressively used in several application areas, particularly to collect data and monitor physical processes. Moreover, sensor nodes used in environmental monitoring applications, such as the aquatic sensor networks, are often subject to harsh environmental conditions while monitoring complex phenomena. Non-functional requirements, like reliability, security or availability, are increasingly important and must be accounted for in the application development. For that purpose, there is a large body of knowledge on dependability techniques for distributed systems, which provides a good basis to understand how to satisfy these non-functional requirements of WSN-based monitoring applications. Given the data-centric nature of monitoring applications, it is of particular importance to ensure that data is reliable or, more generically, that it has the necessary quality.

The problem of ensuring the desired quality of data for dependable monitoring using WSNs is studied herein. With a dependability-oriented perspective, it is reviewed the possible impairments to dependability and the prominent existing solutions to solve or mitigate these impairments. Despite the variety of components that may form a WSN-based monitoring system, it is given particular attention to understanding which faults can affect sensors, how they can affect the quality of the information, and how this quality can be improved and quantified. Open research issues for the specific case of aquatic monitoring applications are also discussed.

One of the challenges in achieving a dependable system behavior is to overcome the external disturbances affecting sensor measurements and detect the failure patterns in sensor data. This is a particular problem in environmental monitoring, due to the difficulty in distinguishing a faulty behavior from the representation of a natural phenomenon. Existing solutions for failure detection assume that physical processes can be accurately modeled, or that there are large deviations that may be detected using coarse techniques, or more commonly that it is a high-density sensor network with value redundant sensors.

This thesis aims at defining a new methodology for dependable data quality in environmental monitoring systems, aiming to detect faulty measurements and increase the sensors data quality. The framework of the methodology is overviewed through a generically applicable design, which can be employed to any environment sensor network dataset.

The methodology is evaluated in various datasets of different WSNs, where it is used machine learning to model each sensor behavior, exploiting the existence of correlated data provided by neighbor sensors. It is intended to explore the data fusion strategies in order to effectively detect potential failures for each sensor and, simultaneously, distinguish truly abnormal measurements from deviations due to natural phenomena. This is accomplished with the successful application of the methodology to detect and correct outliers, offset and drifting failures in real monitoring networks datasets.

In the future, the methodology can be applied to optimize the data quality control processes of new and already operating monitoring networks, and assist in the networks maintenance operations.

Keywords: Dependability, Data quality, Fault detection, Machine learning, Aquatic monitoring

Resumo

As redes de sensores sem fios (RSSF) têm vindo cada vez mais a serem utilizadas em diversas áreas de aplicação, em especial para monitorizar e capturar informação de processos físicos em meios naturais. Neste contexto, os sensores que estão em contacto direto com o respectivo meio ambiente, como por exemplo os sensores em meios aquáticos, estão sujeitos a condições adversas e complexas durante o seu funcionamento. Esta complexidade conduz à necessidade de considerarmos, durante o desenvolvimento destas redes, os requisitos não funcionais da confiabilidade, da segurança ou da disponibilidade elevada. Para percebermos como satisfazer estes requisitos da monitorização com base em RSSF para aplicações ambientais, já existe uma boa base de conhecimento sobre técnicas de confiabilidade em sistemas distribuídos. Devido ao foco na obtenção de dados deste tipo de aplicações de RSSF, é particularmente importante garantir que os dados obtidos na monitorização sejam confiáveis ou, de uma forma mais geral, que tenham a qualidade necessária para o objetivo pretendido.

Esta tese estuda o problema de garantir a qualidade de dados necessária para uma monitorização confiável usando RSSF. Com o foco na confiabilidade, revemos os possíveis impedimentos à obtenção de dados confiáveis e as soluções existentes capazes de corrigir ou mitigar esses impedimentos. Apesar de existir uma grande variedade de componentes que formam ou podem formar um sistema de monitorização com base em RSSF, prestamos particular atenção à compreensão das possíveis faltas que podem afetar os sensores, a como estas faltas afetam a qualidade dos dados recolhidos pelos sensores e a como podemos melhorar os dados e quantificar a sua qualidade. Tendo em conta o caso específico dos sistemas de monitorização em meios aquáticos, discutimos ainda as várias linhas de investigação em aberto neste tópico.

Um dos desafios para se atingir um sistema de monitorização confiável é a deteção da influência de fatores externos relacionados com o ambiente monitorizado, que afetam as medições obtidas pelos sensores, bem como a deteção de comportamentos de falha nas medições. Este desafio é um problema particular na monitorização em ambientes naturais adversos devido à dificuldade da distinção entre os comportamentos associados às falhas nos sensores e os comportamentos dos sensores afetados pela à influência de um evento natural. As soluções existentes para este problema, relacionadas com deteção de faltas, assumem que os processos físicos a monitorizar podem ser modelados de forma eficaz, ou que os comportamentos de falha são caraterizados por desvios elevados do comportamento expectável de forma a serem facilmente detetáveis. Mais frequentemente, as soluções assumem que as redes de sensores contêm um número suficientemente elevado de sensores na área monitorizada e, consequentemente, que existem sensores redundantes relativamente à medição.

Esta tese tem como objetivo a definição de uma nova metodologia para a obtenção de qualidade de dados confiável em sistemas de monitorização ambientais, com o intuito de detetar a presença de faltas nas medições e aumentar a qualidade dos dados dos sensores. Esta metodologia tem uma estrutura genérica de forma a ser aplicada a uma qualquer rede de sensores ambiental ou ao respectivo conjunto de dados obtido pelos sensores desta.

A metodologia é avaliada através de vários conjuntos de dados de diferentes RSSF, em que aplicámos técnicas de aprendizagem automática para modelar o comportamento de cada sensor, com base na exploração das correlações existentes entre os dados obtidos pelos sensores da rede. O objetivo é a aplicação de estratégias de fusão de dados para a deteção de potenciais falhas em cada sensor e, simultaneamente, a distinção de medições verdadeiramente defeituosas de desvios derivados de eventos naturais. Este objectivo é cumprido através da aplicação bem sucedida da metodologia para detetar e corrigir outliers, offsets e drifts em conjuntos de dados reais obtidos por redes de sensores.

No futuro, a metodologia pode ser aplicada para otimizar os processos de controlo da qualidade de dados quer de novos sistemas de monitorização, quer de redes de sensores já em funcionamento, bem como para auxiliar operações de manutenção das redes.

Palavras Chave: Confiabilidade, Qualidade de dados, Aprendizagem automática, Deteção de falhas, Monitorização aquática

Resumo Alargado

Os desastres naturais e provocados pelo homem causam em todo o mundo uma destruição generalizada de bens materiais e serviços, bem como ferimentos e mortes na população. A gestão e os procedimentos de mitigação destes riscos visam reduzir as perdas humanas e a diminuição dos estragos causados pelos desastres. Estas ações de prevenção e mitigação de riscos são tradicionalmente auxiliadas por uma monitorização adequada e meios eficazes de aviso e alerta.

A disponibilidade de sistemas que fornecem informação confiável de fontes de confiança é vital para a proteção de vidas humanas, bem como de bens materiais e naturais. No entanto, soluções para a monitorização em tempo real e a sua integração com os métodos de previsão em tempo real, dos eventos aquáticos potencialmente perigosos, têm que ser otimizadas para os requisitos específicos dos meios aquáticos e até mesmo para os corpos de água individualmente monitorizados. Para isso, as entidades de gestão destes corpos de água, bem como as empresas de serviços públicos relacionados, fazem uso de ferramentas de monitorização *online* e de sistemas de aviso prévio [160] integrados em plataformas inteligentes que apoiam a gestão em tempo real dos ambientes aquáticos tanto nas tarefas do dia-a-dia como em situações de emergência [79]. Neste contexto, a integração das ferramentas de monitorização com redes de sensores sem fios (RSSF) e com sistemas de apoio à decisão baseados na *Web* [160] desempenha um papel vital na monitorização, controlo, atenuação e avaliação do desastre. Na camada de monitorização, as medições individuais e coletivas obtidas pelas redes de sensores devem ser validadas de forma a garantir que existe uma base suficientemente sólida para o aviso prévio. Desta forma, a qualidade e a validade das medições obtidas pelos sensores são requisitos importantes para sustentar o aviso e alerta.

Apesar da existência de vários estudos sobre a deteção de situações anómalas ou faltas em redes de sensores, a maioria destes estudos foca-se em redes de sensores que se encontram em ambientes controlados e em que os dados obtidos através dos sensores representam de forma completa e precisas o sistema monitorizado. Além disso, estes estudos não consideram a presença de fenómenos ou eventos que podem interferir nas medições obtidas pelos sensores [63], ou apenas consideram faltas relacionadas com a comunicação que é feita sem fios [39]. Adicionalmente, as redes de sensores ambientais, como para a monitorização aquática, destinam-se a monitorizar áreas geralmente alargadas [157], podendo ser compostas por vários aglomerados de sensores distando uns dos outros várias centenas de metros. Esta configuração implica geralmente um custo avultado para a operação, de forma a cumprir os requisitos críticos relativos à obtenção de medições precisas, confiáveis e em tempo útil.

Consequentemente, existe uma preocupação de qualidade relativa aos dados obtidos pelas redes de sensores, implicando uma intervenção humana extensa e frequente por parte de técnicos especializados, quer na manutenção periódica dos sensores, quer em tarefas de validação dos dados obtidos. Apesar dos vários estudos na área da confiabilidade de sistemas distribuídos, ou mais especificamente em arquitecturas de computadores para operações confiáveis e em tempo real, os sistemas de monitorização representam vários desafios de confiabilidade [52]. Nestes sistemas, as tecnologias sensoriais e relativas a redes de sensores (agora cada vez mais acessíveis) são vulneráveis perante os vários riscos e podem não ser suficientemente confiáveis e robustas para as condições adversas e factores externos dos ambientes aquáticos. Portanto, nesta tese, a qualidade e a validade das medições obtidas pelos sensores assumem um papel central, sem nunca ignorar os requisitos específicos do ambiente monitorizado.

Para lidar com o problema da qualidade dos dados, é necessário estar continuamente, de forma automática, a caracterizar as medições obtidas. Para isso, a aplicação de técnicas e estratégias com base na exploração de redundância ao nível da camada da obtenção de medições é uma abordagem explorada aqui. Nesta tese, propomos uma metodologia genérica para a monitorização confiável em redes de sensores ambientais, bem como um conjunto de soluções concretas para instanciar esta metodologia em casos de uso reais. A natureza altamente dinâmica das variáveis monitorizadas e a ocorrência incerta de eventos, que afectam o ambiente e os sensores neste incluídos, são impedimentos para a confiança na obtenção de medições com qualidade. Portanto, com a metodologia proposta e as respetivas instanciações, pretendemos colmatar estes impedimentos e com isso atingir três objectivos.

Em primeiro lugar, promovemos a deteção, categorização e correção de medições defeituosas obtidas pelas redes de sensores ambientais. As faltas nestas redes podem ter diversas origens e, consequentemente, afetar os sensores de várias formas, originando diferentes comportamentos de falha que se refletem nas medições obtidas. Devido à multitude de fatores que podem interferir nas redes de monitorização, não existe nenhum processo bem caracterizado para a deteção automática de falhas em sensores, nem para a correção dos respetivos erros nas medições. Além disso, as soluções existentes não consideram a complexidade dos processos monitorizados, nem contemplam todas as falhas típicas que afetam os sensores nestes ambientes adversos.

O segundo objetivo prende-se com a definição de soluções que exploram múltiplas formas de redundância para mitigar o impacto de fatores externos na percepção correta do verdadeiro estado dos sensores e a respetiva análise da verdade subjacente relativa ao ambiente monitorizado. Dada a existência de eventos potencialmente impactantes, é necessário distinguir entre o impacto destes nas medições e as verdadeiras falhas nos sensores. Tipicamente, as soluções de deteção e correção de faltas não consideram a possibilidade de que as medições que aparentem ser defeituosas podem na realidade ser motivadas pelo impacto dos eventos que afetam o ambiente monitorizado. Ignorar estas situações pode levar à deteção incorreta de falhas e, portanto, a falsos positivos. Além disso, as soluções típicas para fusão de dados apenas têm em conta os dados obtidos pelos sensores e não exploram a utilização de outras formas de redundância, como a fornecida por sensores virtuais obtidos através de modelos de simulação e previsão.

Por último, para automatizar os procedimentos típicos para o controlo da qualidade, que incluem uma análise manual dos vários conjuntos de dados obtidos pela rede de sensores para a verificação da existência de falhas nesses dados, é necessário definirmos soluções orientadas à confiabilidade para a automação da avaliação e correção de medições afetadas por erros conjuntamente com a caraterização da qualidade dos dados. Com estas soluções conseguimos melhorar os processos manuais e, adicionalmente, fornecer uma indicação quantitativa sobre a caracterização da qualidade das medições, apropriada para uma perspectiva de confiabilidade.

Para o cumprimento dos objetivos mencionados, procedemos à identificação e caracterização dos vários tipos de faltas que podem afetar os sensores e o funcionamento da rede, bem como o levantamento das soluções existentes para a mitigação dos efeitos das faltas nas medições obtidas. Ainda, tendo em vista a deteção deste comportamentos de falta, avaliámos a adequação de diferentes técnicas de fusão de dados para a modelação do comportamento de sensores, nomeadamente utilizando os filtros de *Kalman*, fusão estatística e redes neuronais para explorar as correlações espaço-temporais existentes entre os sensores de uma rede. Neste contexto, explorámos também a utilização de sensores virtuais, com base em modelos computacionais complexos aplicados especificamente para o ambiente monitorizado, como uma fonte adicional de redundância para melhorar os resultados da fusão de dados.

Com base na caracterização dos vários tipos de faltas e na avaliação das estratégias de fusão de dados, estruturámos a metodologia orientada à qualidade de dados confiável para a definição de sistemas de monitorização ambientais. Esta metodologia proposta divide-se em vários blocos de construção, cuja implementação pode ser feita através da definição e aplicação de estratégias baseadas em aprendizagem automática. Estas estratégias exploram a fusão de dados e, consequentemente, as correlações existentes entre os sensores, para melhorar a qualidade de dados do sistema de monitorização.

A metodologia foi inicialmente avaliada através da sua instanciação e aplicação a diferentes sistemas de monitorização, utilizando conjuntos de dados provenientes de casos de uso reais, para a deteção e correção de *outliers*, *offsets* e *drifts* existentes. A sucessiva validação da metodologia foi efetuada através da comparação da solução baseada na instanciação para a deteção de *outliers* com três técnicas de última geração. Esta validação realizou-se num mesmo conjunto de dados e permitiu comparar a eficácia na deteção de *outliers*. A solução proposta foi pelo menos tão eficaz quanto a melhor das três outras técnicas.

Desta forma, a presente tese endereçou a necessidade de soluções automatizadas para uma qualidade de dados confiável para ambientes aquáticos que podem ser afetados por fatores externos. A metodologia proposta permite assim a implementação de soluções baseadas em aprendizagem automática que detetam de forma eficaz falhas espúrias e sistemáticas em sistemas de monitorização ambientais. Além disso, estas soluções são capazes de lidar com as características altamente dinâmicas das variáveis monitorizadas e, ao mesmo tempo, distinguir as falhas de possíveis ocorrências de fenómenos externos imprevisíveis.

Tendo em conta que as soluções de fusão de dados existentes apenas consideram as correlações entre as medidas dos sensores da rede, esta tese permitiu explorar a inclusão, nas técnicas de fusão de dados, de informação relacionada com o ambiente monitorizado a fim de melhorar o processo de fusão. Com a disponibilidade de modelos de simulação e previsão para o ambiente em questão, somos capazes de caracterizar quais os sensores que oferecem melhor nível de correlação relativamente a cada sensor, possibilitando uma melhor eficácia no emprego das técnicas de aprendizagem automática. Esta informação adicional e a possível utilização de sensores virtuais (para além dos sensores físicos) permitem-nos obter melhores resultados na fusão dos dados dos sensores que, consequentemente, suportam uma melhor distinção entre eventos e falhas.

Por fim, um dos blocos da metodologia proposta é dedicado à estimação e quantificação da qualidade para cada medição obtida pelos sensores. Esta qualidade é caracterizada por um coeficiente que reflete também o estado do sensor. O coeficiente é determinado com base nas estratégias de aprendizagem automática para a fusão de dados e tem em consideração a existência de falhas no sensor em questão. Esta contribuição é uma inovação nas soluções de deteção e correção de falhas.

Contents

List of Figures

List of Tables

List of Publications

The following is a list of publications containing the work presented in this thesis as well as some additional results.

1. **Gonçalo Jesus**, António Casimiro, and Anabela Oliveira. Towards dependable measurements in coastal sensors networks. In *European Workshop on Dependable Computing*, pages 190–193. Springer, 2013

2. **Gonçalo Jesus**, Anabela Oliveira, and António Casimiro. Ensuring reliable measurements in remote aquatic sensor networks. In *2014 International Conference on Hydroinformatics*. CUNY Academic Works, 2014

3. **Gonçalo Jesus**, Anabela Oliveira, Alberto Azevedo and António Casimiro. Improving sensor-fusion with environmental models. In *2015 IEEE SENSORS*, Busan, pages 1–4. IEEE, 2015

4. **Gonçalo Jesus**, António Casimiro, and Anabela Oliveira. A survey on data quality for dependable monitoring in wireless sensor networks. *Sensors*, 17(9):2010, 2017

5. **Gonçalo Jesus**, António Casimiro, and Anabela Oliveira. Dependable outlier detection in harsh environments monitoring systems. In *Computer Safety, Reliability, and Security – SAFECOMP 2018 Workshops, ASSURE, DECSoS, SASSUR, STRIVE, WAISE, and ICCS, Trento, Italy, September 18, 2018, Proceedings*, pages 224–233. Springer, 2018

The following list contains all the publications during the period of the thesis regarding related work in which the author participated but it was not included here.

1. **Gonçalo Jesus**, João Gomes, NA Ribeiro, and Anabela Oliveira. Custom deployment of a Nowcast-forecast information system in coastal regions. In *Proceedings of Geomundus*. 2012

2. Anabela Oliveira, LM David, M Rodrigues, **Gonçalo Jesus**, J Rogeiro, J Costa, JL Gomes, JP Fernandes, JS Matos, F Ferreira and others. Sistema Inteligente de Apoio à Gestão Avançada de Sistemas Urbanos de Aguas Residuais. LNEC, 2012

3. Luís Mesquita David, Anabela Oliveira, José Saldanha Matos, Pedro Póvoa, José Menaia, R Carvalho, Marta Rodrigues, **Gonçalo Jesus**, André B Fortunato, Carla Rodrigues and others. Metodologia de desenvolvimento de sistemas integrados de alerta em tempo real da qualidade de águas estuarinas. APRH, 2012

4. Marta Rodrigues, J Costa, **Gonçalo Jesus**, AB Fortunato, J Rogeiro, JL Gomes, Anabela Oliveira, and LM David. Application of an estuarine and coastal nowcast-forecast information system to the Tagus estuary. In *6th SCARC*. 2013

5. Alberto Azevedo, S Boer, **Gonçalo Jesus**, JL Gomes, Anabela Oliveira, AB Fortunato. Sistema computacional de alta resolução para planeamento e resposta a derrames de hidrocarbonetos em aplicações oceânicas, costeiras e estuarinas. *Congresso das Zonas Costeiras 2013*, 2013

6. Anabela Oliveira, L David, M Rodrigues, J Santos, P Póvoa, C David, JS Matos, F Ferreira, **Gonçalo Jesus**, J Costa and others. Sistema de previsão em tempo real da dinâmica e qualidade da água de sistemas de drenagem urbanos e respetivos meios recetores. In *Proceedings of SILUSBA*. 2013

7. Alberto Azevedo, **Gonçalo Jesus**, JL Gomes, Anabela Oliveira, and AB Fortunato. RDFS-PT: A nowcast-forecast system for high resolution coastal applications. In *Book of Abstracts of The Future of Operational Oceanography 2013 Conference*. 2013

8. Luís Mesquita David, Anabela Oliveira, Marta Rodrigues, **Gonçalo Jesus**, Pedro Póvoa, Conceição David, Ricardo Costa, AB Fortunato, José Menaia, A Frazão, and others. Development of an integrated system for early warning of recreational waters contamination. In *NOVATECH 2013*. GRAIE, 2013

9. Marta Rodrigues, LM David, Anabela Oliveira, AB Fortunato, J Menaia, J Costa, T Mota, J Rogeiro, **Gonçalo Jesus**, P Morais and others. Deliverable 4.3. 4-On-line monitoring of CSO: sewer and receiving waters. *PREPARED Project Deliverable*. 2013

10. **Gonçalo Jesus**, JL Gomes, Anabela Oliveira, S Boer and Alberto Azevedo. From a nowcast-forecast information system to an oil spill risk assessment and response tool. In *Proceedings of Geomundus*. 2013

11. João Gomes, Marta Rodrigues, Alberto Azevedo, **Gonçalo Jesus**, João Rogeiro and Anabela Oliveira. From a nowcast-forecast information system to an oil spill risk assessment and response tool. In *2013 Eighth International Conference on Broadband and Wireless Computing, Communication and Applications*, pages 518–523. IEEE, 2013

12. Anabela Oliveira, J Rogeiro, **Gonçalo Jesus**, AB Fortunato, LM David, M Rodrigues, J Costa, T Mota, JL Gomes and RS Matos. Deliverable 4.3. 5 Real-time monitoring and forecast platform to support early warning of faecal contamination in recreational waters. 2014

13. Luís Mesquita David, Anabela Oliveira, Marta Rodrigues, AB Fortunato, J Rogeiro, **Gonçalo Jesus**, T Mota, J Costa, J Menaia, P Póvoa, and others. Real-time monitoring and forecasting system for early warning of recreational waters contamination. 2014

14. Rafaela Matos, F Ferreira, J Saldanha Matos, Anabela Oliveira, L David, M Rodrigues, **Gonçalo Jesus**, J Rogeiro, J Costa, T Mota, and others. Implementation of an early warning system in urban drainage infrastructures for direct discharges and flood risk management. *WIT Transactions on The Built Environment*,139. WIT Press, 2014

15. Alberto Azevedo, André B Fortunato, Bruno Epifânio, Sérgio den Boer, Eduardo R Oliveira, Fátima L Alves, **Gonçalo Jesus**, João L Gomes, Anabela Oliveira. WIFF - Oil spill forecast framework: application to the Aveiro lagoon. In *13th International Workshop on Multiscale (Un)-structured mesh numerical ocean modeling* LNEC, 2014

16. Marta Rodrigues, Anabela Oliveira, AB Fortunato, H Queiroga, LM David, V Brotas, J Costa, J Rogeiro, **Gonçalo Jesus**, JL Gomes, and others. Management of estuarine and coastal ecosystems: observatories as effective tools to predict and anticipate changes. In *ECSA 54 Conference - Coastal systems under change: tuning assessment and management tools.* LNEC, 2014

17. Marta Rodrigues, André B Fortunato, Bruno Epifânio, Sérgio den Boer, **Gonçalo Jesus**, João L Gomes, Anabela Oliveira. A real-time water quality model of the Tagus estuary. In *13th International Workshop on Multiscale (Un)-structured mesh numerical ocean modeling.* LNEC, 2014

18. Marta Rodrigues, Anabela Oliveira, LM David, AB Fortunato, J Costa, J Rogeiro, JL Gomes, **Gonçalo Jesus**, T Mota, P Póvoa, and others. Real-time observatory of

the water quality in the Tagus estuary. Operational Oceanography for Sustainable Blue Growth. In *Proceedings of the Seventh EuroGOOS International Conference*, pages 535–544. 2014

19. Alberto Azevedo, André B Fortunato, Bruno Epifânio, Sérgio den Boer, Eduardo R Oliveira, Fátima L Alves, **Gonçalo Jesus**, João L Gomes, Anabela Oliveira. WIFF - A Nowcast-Forecast system for high-resolution coastal applications. In *Proceedings of the Seventh EuroGOOS International Conference*. 2014

20. Anabela Oliveira, **Gonçalo Jesus**, JL Gomes, J Rogeiro, A Azevedo, M Rodrigues, AB Fortunato, JM Dias, LM Tomas, and L Vaz and others. An interactive WebGIS observatory platform for enhanced support of integrated coastal management. *Journal of Coastal Research*, 70(sp1):507–513. BioOne, 2014

21. Luís M David, Anabela Oliveira, Marta Rodrigues, André B Fortunato, José Menaia, Pedro Póvoa, Conceição David, Filipa Ferreira, Joana Costa, Tiago Mota, and others. Plataforma de previsão e monitorização em tempo real para gestão operacional de sistemas de drenagem urbana. LNEC, 2014

22. Tiago Mota, LM David, A Rocha, **Gonçalo Jesus**, Anabela Oliveira. Assessment of the flow predictions from a large urban drainage model forced by distinct spatial resolution weather forecasts. LNEC, 2014

23. João L Gomes, **Gonçalo Jesus**, João Rogeiro, Anabela Oliveira, Ricardo Tavares da Costa, André B Fortunato. Molines-towards a responsive web platform for flood forecasting and risk mitigation. In *2015 Federated Conference on Computer Science and Information Systems (FedCSIS)*, pages 1171–1176. IEEE, 2015

24. João L Gomes, **Gonçalo Jesus**, João Rogeiro, Anabela Oliveira, Ricardo Tavares da Costa, André B Fortunato. An Innovative Web Platform for Flood Risk Management. In *International Conference on Innovative Network Systems and Applications*, pages 217–231. Springer, 2015

25. Marta Rodrigues, **Gonçalo Jesus**, J Rogeiro, AB Fortunato, JL Gomes, Anabela Oliveira. RealQual: Towards real-time high-resolution monitoring and prediction of water quality in estuaries and coastal areas. LNEC, 2015

26. Luis David, M Rodrigues, AB Fortunato, Anabela Oliveira, T Mota, J Costa, J Rogeiro, **Gonçalo Jesus**, JL Gomes, J Menaia, and others. Demonstration system for early warning of faecal contamination in recreational waters in Lisbon. *Climate*

Change, Water Supply and Sanitation: Risk Assessment, Management, Mitigation and Reduction. IWA Publishing, 2015

27. Paula Freire, AB Fortunato, Ana Rilo, K Li, R Costa, Anabela Oliveira, **Gonçalo Jesus**, JL Gomes, J Rogeiro, P Pinto, and others. Project Molines: Modelling floods in estuaries. From the hazard to the critical management-Final Report. LNEC, 2016

28. Alberto Azevedo, André B Fortunato, Bruno Epifânio, Sérgio den Boer, Eduardo R Oliveira, Fátima L Alves, **Gonçalo Jesus**, João L Gomes, Anabela Oliveira. An oil risk management system based on high-resolution hazard and vulnerability calculations. *Ocean & coastal management*, 136:1–18. Elsevier, 2017

29. André B Fortunato, Anabela Oliveira, João Rogeiro, Ricardo Costa, João L Gomes, Kai Li, **Gonçalo Jesus**, Paula Freire, Ana Rilo, Ana Mendes, and others. Operational forecast framework applied to extreme sea levels at regional and local scales. *Journal of Operational Oceanography*, 10(1):1–15. Taylor & Francis, 2017

Chapter 1

Introduction

1.1 Background

Natural and man-made disasters worldwide cause widespread destruction of property, human injuries and deaths. Risk management and hazard mitigation procedures aim to reduce human losses and diminish the damages related to these disasters. In fact, risk management is a consequence of three fundamental aspects: i) a structure is always a potential hazard, ii) natural hazards are unpredictable and iii) the necessity to guarantee the safety of the population, in case of a hazard. Moreover, hazards prevention and mitigation actions are greatly supported by adequate monitoring and timely early warning.

Recently, the processes of event detection, early alert and population warning have evolved from traditional approaches, to be assured by automated systems, with more or less human assistance. SAGE-B [61], for instance, was developed to support all fundamental data related to dams and to the emergency elements in case of a dam-break flood, such as the dynamic information about the population in the areas at risk or the rescue vehicles located in the predicted flooded areas. Information systems such as the one mentioned can also be used for natural floods, accounting for existence of the protection structures (dikes and levees) and the flooding events resulting from their breach and failure, forced by multiple drivers (river flows, storm surges, sea waves) that can induce floods from the hydrographic basin to the coast.

Unfortunately, many disaster management systems worldwide suffer significant functional limitations, due to the difficulties in accessing realtime monitoring data overcoming unreliable and inconsistent multiple-source information, and dealing with insufficient capacity for sharing this information across multiple emergency actors [137]. For instance, in a natural or man-induced flood, the factors that influence the exposure can be evaluated before the event [72] through prediction of the water dynamics [69], which can be anticipated. Therefore, any limitation in information management has negative impacts on the quality of decision-making and hence on the success of disaster response.

The availability of systems delivering reliable information from dependable sources is vital for the protection of human lives as well as material and natural assets. Anticipating the occurrence or early detecting hazardous events in real-time is the most optimal way to ensure an appropriate and timely response. However the methodology for real-time monitoring and its support to real-time forecasting of the hazardous events should be optimized for the requirements of specific water-related problems and even of individual water bodies. Water management entities and utilities worldwide therefore employ on-line monitoring tools and early warning systems [160], integrated into intelligent platforms that support real-time management of water systems both for daily tasks and in emergency situations [79].

Frequently, danger events occur due to combined sources of danger. Additionally, the approaches used for one type of event cannot be used for other events as their characteristics and risk requirements are distinct. Floods will be taken as an example, which is one of the major natural hazards in most of the countries around the world. The focus of most past flood analysis has been the slow-onset fluvial floods and the combination of surge and tidal floods (especially in areas where coastal flood risk is high), which are simpler to monitor and predict. However, many countries face dangerous risks with other types of floods, most associated with human activities, such as urban drainage floods, flash floods, dam (artificial and natural) break floods or even ice-ham back water floods [131]. A common denominator is the need for robust, timely and dependable data on the forcing factors on the consequences in the field.

Although it is possible to forecast most physical phenomena accurately (at least at large scales), dependable real-time monitored data, such as water level, flow or precipitation, is essential in order to confirm predictions and to support the issuing of alerts and support decisions on mitigation measures to be performed in areas at risk. Phenomena forecasting and monitoring, simulation, evaluation and analysis of the derived risks are of the utmost importance in losses prevention.

Integrating wireless sensors and web-based decision support systems [160] plays a main role in monitoring, controlling, relieving, and assessing disasters. This combination together with large-scale computation either for forecasting/simulations or data analysis, facilitates decisions needed to manage environmental threats.

The time dimension is critical for such systems. All the components of risk management system operate within a constrained time frame, which is desirably short, for the successful protection of people and assets. When an alarm response time exceeds the target response time, warnings are useless. Furthermore, because disaster-warning applications are safety critical and might carry significant financial penalties and loss of human lives in case of failure, they must meet all the appropriate criticality constraints.

They should be able to tolerate both hardware and software failures and not fail at critical moments in any of the tiers. Forecast simulations may also present errors due to insufficient physics, poor numerical formulations, inadequate model applications or cascading errors from the long scale atmospheric modeling down to the water dynamics at the scale of interest. On the monitoring side, which in turn support the simulation results, the individual and collective readings from the network of sensors on-site must be validated in association with the simulation results, in order to sustain a scientific basis for the early warning. Therefore, the quality and validity of monitored measurements is an important component for the warning and alert issuing.

However, when monitoring harsh environments, the deployed sensors have to perform under unfavorable conditions, producing several types of uncertainties:

- Measurements may be imprecise, incorrect, incomplete, incoherent or inappropriate to the problem at hand;
- Ambiguous observations (for instance if another object or event interferes with the one in question);
- Reduced or limited representation of the reality.

Most of these situations happen from sensor malfunction due to continuous exposure to the environment or negative impact of environment-related phenomena. Though the goal of detecting faulty situations in sensor networks is a well-known research subject, the majority of the works in this area is focused on controlled environment setups, where the sensors represent a reliable view to the monitored system. Additionally, these works do not consider the presence of environmental interference events on sensor measurements [63], while other studies that consider it are mainly focused on wireless communication faults [39].

Therefore, increasing sensor data quality in the scenarios of environment monitoring networks is an important asset for the stakeholders, with particular challenges that are not studied in most of network setups. In these setups, the operational conditions are challenging and ensuring their reliability is often hard or costly, with severe consequences to sensor data collection or the sensor data itself.

Environment network setups are meant to monitor and cover a usually large area [157], being comprised of clusters of sensors widespread, sometimes with hundreds of meters distance between them. This setup requires large maintenance operations costs in particular to maintain tight requirements in providing accurate, reliable and timely information to assist the stakeholders. This availability, coupled with reliability, of the near real-time monitoring information is a difficult requirement in real implementations of monitoring networks. Building and maintaining these high-quality data networks is thus a complex and challenging task.

1.2 Motivation

A reliable continuous flow of real-time data is dependent on complex and powerful forecast systems that are now able to predict environmental variables such as storm events with small errors. Reliable real-time monitoring data, such as surface water elevation, flow or water quality variables rely on the sensor hardware and the communication networks in place at the physical environment (oceans, river, lakes, etc.) and its proper maintenance.

The effectiveness of existing emergency warning and forecast procedures for natural and man-made hazardous events may thus be limited by several factors, including an often sparse and unreliable real-time observational network, use of coarse-resolution prediction models, and the reliance on traditional approaches to convey warning and forecast information.

Ensuring the quality of monitoring data is fundamental to avoid false alarms or to ignore relevant data. However, because these sensors are located in the physical environment, they are constantly being subjected to factors that directly interfere with the data quality, such as potentially strong currents, debris accumulation and tough weather conditions. Consequently, there is a trust issue related to the collected data, which demands an extensive human intervention in terms of time and knowledge specialization, data validation tasks and periodic maintenance of sensors.

In fact, several authors confirmed that environment monitoring networks datasets contain a relatively large presence of faulty data. In [155], the authors verified that the range of faulty data can reach up to 20% of outputted sensors datasets, which include multiple types of errors. Also, in another experiment including a 33 sensors network deployed in a forest for the period of 44 days [171], 51% of the collected data contained different data anomalies. Similar conclusions to the previous studies were reached in the Great Duck Island deployment [161], where data from each sensor was considered faulty in a range from 3% to 60%.

In spite of the vast research on the dependability of distributed systems, in particular on computational architectures/frameworks for reliable and timely operations, monitoring systems pose new challenges to dependability [52]. The sensory and sensor network technologies, that are now becoming widely available, are subject to diverse hazards and may not be sufficiently reliable and robust against harsh exogenous and/or environmental factors. There is still a lack of architectural, fault-tolerance and system management solutions, which are essential for dependable, robust remote monitoring, necessary for adequate water management.

There is a need to support the stakeholders with tools that allow a better decision-making, by combining robust, reliable and validated sensor networks, which may integrate both conventional (expensive) and novel (low-cost) sensor nodes of wireless sensor networks. Herein, the validity of the sensing information assumes a central role without neglecting the specific requirements of the monitored environment.

To deal with this problem it is necessary to continuously and automatically characterize the quality of collected data. Therefore, the application of techniques based in the existence of redundancy at the data collection and data processing levels is a promising approach.

1.3 Objectives and approach

This work aims at the design and validation of a general methodology that frameworks data quality-oriented solutions for dependable monitoring in environmental sensor networks.

The methodology aims at fulfilling three objectives. The main objective is to detect, categorize and correct faulty measurements in environment monitoring sensor networks. Faults in both sensors and networks have different natures and consequently produce different outputs in the respective measurements datasets. In the context of environment monitoring networks, due to the multitude of external factors that may interfere with the sensor readings, there is not a well-defined process to automatically produce a correction or an estimation to replace the faulty measurement. Current solutions either do not contemplate all types of failures or are not adequate to environment monitoring networks.

The second objective is the analysis of the impact of the environment in the monitoring network and, specifically, in the sensors measurements. Moreover, focusing on the effects of environmental factors in sensing data, there is a particular interest in the environmental-related and impactful events, and its distinction from sensor failures. Generally, faults detection and correction solutions do not account for the presence of external events, which eventually may lead to false positive detection situations.

Finally, the third objective is the automated analysis of the data quality, regarding sensor readings. The typical quality control procedures include a manual overview of the network datasets to analyze correlated sensors and the existence of failures within those datasets. Given the nature of such procedures, one of the requirements for its execution is the expert-knowledge on the monitoring site and network deployment. The automation of the quality control and subsequent data quality evaluation can be performed using the intelligent establishment of sensors correlations and the detection of existing failures.

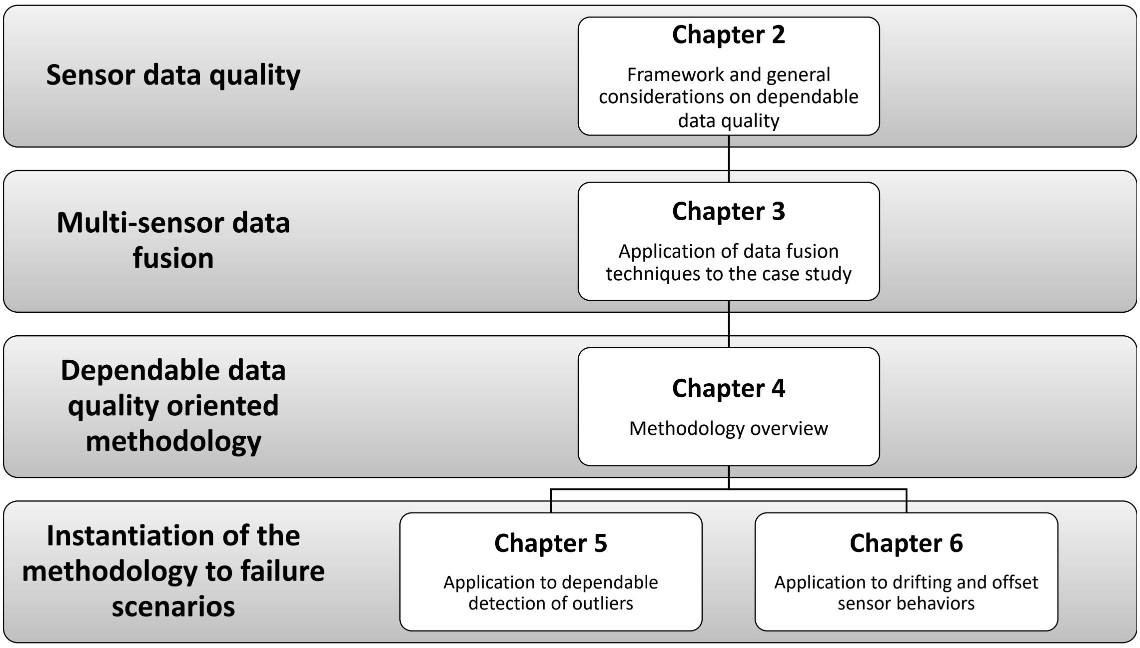

Figure 1.1: General framework of the work.

To address the problem considered in this thesis and achieve the stated objectives, we defined an approach including the following steps, also outlined in Figure 1.1:

- Identification and characterization of existing solutions to dependable monitoring in sensor networks, through the analysis of the several types of faults that affect the sensors and network operation, and the respective strategies to mitigate the effects on sensor data and relevant failure modes;

- Gathering of the effects of the aquatic environment and related phenomena on the sensors deployed on those environments;

- Evaluation of the feasibility of data fusion strategies based on machine learning for the modeling of sensors behavior through the exploitation of spatiotemporal correlations between neighbor sensors within a sensor network. And study of the introduction of environment-specific and complex computational model products as a redundancy strategy to improve data fusion results;

- Design of a dependable data quality oriented methodology for the application to environmental monitoring systems, that are subjected to harsh and highly dynamic conditions. The aim is to provide a basis to increase data quality in sensor networks, considering intelligent techniques that explore and analyze the correlations between neighbor sensors;

- Evaluation of the methodology through the application and setup of the methodology in building specific solutions for various datasets and types of failures;

- Validation of a solution according the proposed methodology, based in machine learning data fusion, in particular using artificial neural networks, for the detection and correction of outliers, drifts and offsets in sensor networks datasets.

1.4 Contributions

With the overall goal of presenting a set of procedures that underline the need for automation and intelligent perception of affecting factors in the design of solutions for failure detection and mitigation in environmental sensor networks, the work herein provides the following contributions as an advance to the state-of-the-art:

- The problem decomposition, namely the efficient detection of the failure modes via a new generically applicable methodology to environment monitoring networks (systems that may be subject of unpredictable external phenomena). Although works on fault detection are common, there is a overall emphasis on outliers when other types of failures are relatively ignored and dealt with lightly. The proposed procedures enable the detection of sensor faults affecting sensor measurements, using machine learning techniques;

- The inclusion of environment-related information in the sensor data fusion mechanism, in order to improve the overall fusion process. Existing approaches ignore this type of information, using mainly the sensor measurements and its inherent correlations. This traditional approach may impact negatively the fusion result either by the possible masking of undetected failures in neighbor sensors or by ignoring false positive failures information in relevant sensors. Such information is processed by the data fusion approaches generating false outcomes on both detection and correction mechanisms. A methodology proposed in this thesis, comprising fusion approaches with relevant information, provides a monitoring data quality increase when comparing to the typical methods;

- A data quality coefficient is assigned to each new measurement. Typically, failure detection and correction solutions are only focused on producing a corrected value or detecting a failure occurrence disregarding the associated quality of the outcome. In the proposed methodology, the quality coefficient is dynamically attributed to each new measurement based on the methods used to detect and correct failures, considering not only their outcome but also additional information regarding neighbor sensors performance, including in particular if there is any failure affecting its measurements.

1.5 Structure of the document

The document is structured in seven chapters. The initial and present chapter, Chapter 1, corresponds to a general introduction of objectives, final contributions and general context.

An overview of the following chapters and their sequence is highlighted in Figure 1.1, from the problem statement to the definition of the methodology proposed herein and its instantiations.

In Chapter 2 an extensive perspective of the multiple sides of sensor data quality issues in monitoring sensor networks is presented. This chapter has a clear focus on the dependability aspects concerning the sensor devices, the interconnecting network, and the resulting monitoring data to further processing systems. Additionally, multiple sensor networks datasets are presented, and in particular the thesis case study is described.

Chapter 3 discusses the importance of sensor data fusion with the goal of increasing data quality. Several applications of data fusion techniques are presented, mainly in the context of modeling sensor behaviors and learning environment dynamics.

In Chapter 4 a novel dependable data quality oriented methodology is proposed for environmental monitoring sensor networks.

Chapter 5 instantiates the methodology from Chapter 4 to setup and validate a new solution for the detection and correction of outliers (ANNODE) in two different environments.

While in the previous chapter the focus is on outliers, Chapter 6 focuses on failures that are systematic or continuous during a determined period of time, in particular the detection of drifts and offsets.

Finally, Chapter 7 states the conclusions drawn from the study and proposes possible directions for future lines of research.

Chapter 2

Context and state-of-the-art

2.1 Introduction

In order to increase the dependability of monitoring applications in wireless sensor network (WSN) settings, one must be aware that the quality of monitoring data can be affected by faults. In essence, there is a problem of data quality assurance, which can be faced taking two main perspectives: by deploying dependability techniques to handle faults and enforce the reliability of the system, or by enhancing the system with means to continuously assess and characterize the quality of data [41]. In the former case, the system will not be aware about the quality of data. Therefore, if a certain quality is needed, it must be enforced by design, confining the effects of faults a priori. Considering sensors to be one of the main sources of data, errors in sensing measurements are handled by procedures that are established based on a deep understanding of the characteristics of the sensors [64]. For instance, missing readings may be handled by oversampling, while outliers and noise can be handled through averaging over a window of samples. In the latter case, the system will be aware of data quality through the use of data analysis techniques and will then be able to adapt its behavior or apply mitigation measures when this quality is deemed not adequate. For instance it may be possible to exploit knowledge about the physical processes being monitored to determine appropriate data corrections in order to obtain the needed data quality. Given that no system can be built to exhibit 100% reliability, the two perspectives can be combined. In this chapter, the latter perspective was selected considering that the quality of sensor data can be assessed, providing an indication of the overall system health, encompassing sensors, the wireless network and the processing tasks.

Assuring the quality of sensor data for a dependable operation is particularly challenging in some WSN-based monitoring applications. In fact, it is often the case that the sensors and the WSN are deployed in harsh environments and exposed to extreme physical conditions, thus being more likely affected by faults. The problem becomes critical when dependability is an important application requirement. For instance, in water-related information systems, inaccurate information in aquatic monitoring may lead to false warnings being issued, or harmful situations not being detected early enough (e.g., floods or pollution events) [150]. Therefore, ensuring the accuracy of collected data is also necessary for effectiveness reasons. In this example, the operational conditions are typically hard to accurately predict, ensuring the reliability of operations is often hard or costly, and the consequences of inaccurate sensor data collection can be severe.

Herein, existing solutions to assure dependable monitoring in WSNs are characterized and systematized in a two steps procedure. In the first step, the root cause of dependability problems is analyzed concerning the quality of sensor data. Moreover, several kinds of faults that may affect the system operation are identified, in particular at sensor and network levels, with their effect on sensor data and in the relevant failure modes [57]. When appropriate, mitigation solutions for the adjustment of the sensors measurements according to each disturbance are referred. Then, a comprehensive overview is provided regarding solutions to achieve improved sensor data quality and a dependable operation of WSN-based monitoring applications. In addition to detection and correction strategies, fault-tolerance strategies based on sensor data fusion procedures are portrayed, exploiting the availability of redundant measurements or available modelling surrogates. However, we only overview works and solutions related to monitoring in aquatic environments, noting that these solutions are also applicable in many other contexts, but that the opposite might not be true, in particular concerning solutions that are not agnostic to the semantics of the monitored data.

The chapter is organized as follows. Section 2.2 describes the concept of data quality and the main aspects that may affect this quality during monitoring. Section 2.3 presents an overview on solutions for dependable sensor networks. Section 2.4 introduces the applications that motivated this study, and the open research issues associated with it. Section 2.5 discusses the existence of datasets for fault detection and aquatic environment monitoring datasets. The chapter concludes in Section 2.6, with a discussion on the possible results from the solutions mentioned herein.

2.2 Sensor data quality

When the quality of sensor data is an important attribute for the dependability of the application, it becomes necessary to express this quality through indicators, which can be done in various ways. Additionally, a priori knowledge about the possible causes of quality degradation, translated into faults and a corresponding fault model, is also relevant. This knowledge will enable a more accurate characterization of the quality of sensor data. Moreover it enables to incorporate in the system techniques to mitigate the effects of specific faults, assumed in the fault model. These aspects are addressed in the following sections.

2.2.1 Dependability strategies

When designing a fault-tolerant and dependable system, the typical means to deal with system errors and faults include error detection and fault handling. In this context, endowing the system with redundant components can be instrumental to compensate existing errors or faults affecting a component. The affected component can be replaced in its tasks by the spare, redundant component, which will ensure that the system function will remain being provided. However, redundancy does not refer solely to having multiple similar hardware and/or software components, which is just one type of redundancy. There are also forms of redundancy in the time (e.g., repeating some action multiple times) and in the value domains (e.g., adding extra information) [174].

Some examples of space redundancy include storing information in several disks, machines or data centres, having multiple nodes performing the same computation (either in parallel, called active replication, or with some nodes in stand-by mode, called passive replication), or sending a network message through multiple network paths [26].

Temporal redundancy is typically explored in reliable communication systems that retransmit messages when they suspect that these messages might have been lost in previous transmissions. Restarting an aborted transaction or a deadlocked computation are also examples of temporal redundancy [108].

Lastly, redundancy in the value domain, sometimes referred to as data or information redundancy, is observed in data storage and communication systems that use error correcting codes associated to the stored or transmitted data, allowing the original information to be reconstructed when some bits or parts of the information become corrupted [108]. To deal with malicious forms of information corruption, cryptographic signatures may be used.

In the application of these concepts to sensor validation, [91] stated that there are two classical approaches widely used: a) analytical redundancy and b) hardware redundancy. Analytical redundancy uses mathematical relationships between measurements to predict or infer a sensor's value. One disadvantage of this approach is the possible inefficiency of the mathematical processes when there exists a large number of sensors and the model complexity increases. Another disadvantage is the fact that the mathematical relationships can be very data specific and a slight modification may require significant efforts. Hardware redundancy is not always possible because of the costs implied by additional sensors and their installation and maintenance operations.

The most adequate approach to be used depends on several issues, like the assumed fault model, the criticality of the application sensors, cost or timeliness requirements. In some cases, several dependability techniques can be used in a single system to deal with different problems or to achieve the needed levels of assurance. This is particularly true in complex systems, like the ones considered in this thesis, in which different techniques can be applicable to mitigate faults in the sensing process and to handle WSN faults. Combinations of the solutions mentioned ahead in this chapter (Section 2.3.1) may thus be used in the design of a single system.

2.2.2 Expressing data quality

The interpretation and modelling of the available information into adequate frameworks is the main way to characterize the quality of the obtained sensor data. Data quality has been identified through several, often overlapped, indicators:

- **validity -** is typically employed when a specific requirement about the quality of data is available, against which is feasible to compare some quality measure and declare if the data is valid [41; 147].

- **confidence -** is an attribute that may be elaborated from the continuous observation of sensor data, without the need for a quality requirement to be available. Generally used when data sets are available and can be characterized in a probabilistic way, along with model fitting or threshold definition techniques, to yield continuous or multi-level confidence measures [71].

- **reliability -** is a typical dependability attribute [28], expressing the ability of a system to provide correct service (or correct data, for the matter) over a period of time. The term data reliability in sensor networks is often considered when transmissions and/or communications may be subject to faults like omissions or total crash [115; 188].

- **trustworthiness -** is mostly employed in connection with security concerns, namely when it is assumed that data can be altered in a malicious way. In the context of sensor networks, it characterizes the degree to which it is possible to trust that sensor data has not been tampered with and has thus the needed quality [170].

- **authenticity -** is also used, in particular, in a security context, but to express the degree to which it is possible to trust on the claimed data origin [31]. This is particularly important when the overall quality of the system or application depends on the correct association of some data to its producer.

This characterization does contain other terms that are implicit to the above indicators. Herein the diverse typologies of data quality are described along with the procedures to obtain a quality parameter, either for each individual sensor or for the global system, according to several studies. So, in terms of applicability, single-sensor validity must be derived from multi-sensor fusion validity, thus a separate analysis is needed.

In single-sensor situations, there are models and related information that support the reasoning about an individual sensor's data quality without requiring other sensors' data. Different fault detection methods include:

- Rule-based methods - use expert knowledge about the variables that sensors are measuring to determine thresholds or heuristics which the sensors must comply.

- Estimation methods - define a "normal" behavior by considering spatial and temporal correlations from sensor data. A sensor reading is matched alongside its forecasted value to assess its validity.

- Learning-based methods - define models for correct and faulty sensor measurements, using collected data for building the models.

These methods were used in many applications. For example, in [155], such methods help identify faulty sensor data such as noise and outliers in chlorophyl concentration sensors applied to lakes. In this example, all the three methods were used to assert the correctness (or incorrectness) of the collected data, adopting a Boolean approach to quality characterization. However, the same methods may be employed in other ways, as means to characterize quality in a step-wise or even continuous way. For instance, and still considering a single-sensor situation, [71] employed fuzzy logic rules to obtain a qualitative sense of a sensor's validity based on its own historical behavior represented by a confidence measure.

In a multi-sensor situation, the quality of sensor measurements is characterized by using redundant or correlated data obtained from the different sensors. This redundancy allows for data fusion methods to be deployed at the network level, resulting in improved (fused) sensor data as well as improved data quality characterization.

Sensor data fusion methods will be detailed in Section 2.3. As for the quality characterization process when data fusion is performed, the methodology to be applied depends on the available information concerning the quality of individual sensor measurements. In fact, this information can also be used in the data fusion process itself.

For instance, in [71] the approach relied on a statistical method (Parzen estimation of probability density function) to determine the variance of sensors data and calculate the average value, considering just the sensors with high-quality standard in the data fusion process. If all sensors are producing high-quality data, then the fusion will also reach the highest possible quality. Otherwise, better results will be achieved when discarding sensor data with quality below a threshold, rather than using these data in the fusion process.

Regarding the quantification of data quality, the two main approaches consist in considering discrete quality classes or continuous quality values.

In the discrete approach, it is possible to use binary classes, such as {valid, invalid} [77], or use a multi-level class, like {very low, low, high, very high} [71]. These discrete classifications can be applied to each sensor (individual sensor data) or to the whole network of sensors (fused data).

In the continuous approach, a confidence level is usually derived, ranging in a well-defined continuous interval (often $[0, 1]$ or equivalently $[0\%, 100\%]$). So, the validity of sensor information may not only have the values "true" or "false", especially if one must process continuously valued data [41; 91]. For instance, a noisy sensor (internal or external noise) may deliver useful data within some error margin, but the quality of that data is lower than that from a non-noisy sensor. In a multi-sensor fusion application, the quality quantification can be calculated using a cumulative association of each sensor quality coefficient [127] that increases with the importance of the measurement provided by a reliable sensor and decreases with those which are anomalous. Another solution may be to calculate the percentage of sensors used in the fusion against the total number of sensors in the network.

2.2.3 Sensor level faults

In this subsection a systematization of the main types of sensors and their characteristics, classifying the various data errors that may be produced by sensors, is presented. From the perspective of building modular dependable systems, the several possible faults and the consequent data errors are grouped into well-defined sensor failure modes. Therefore, relevant failure modes are identified under which a sensor can fail and produce data with degraded quality. The focus herein is on the sensor level, whereas the next subsection addresses network level faults. Finally, this section also addresses possible mitigation techniques to handle sensor faults.

2.2.3.1 Sensor model

Sensors are the front-end devices of the systems that collect real-world environmental parameters, e.g., pressure, temperature, humidity, etc. These devices generate an electrical output proportional to the measurand (the physical quantity of interest, e.g., pressure, temperature that is applied to the sensor) [132], responding to a stimulus. The stimulus is the quantity, property, or condition that is received and converted into an electrical signal. Generally, measurand has the same meaning of stimulus, although it can be applied when referring to a quantitative characterization.

A sensor itself is part of a larger system that may incorporate many other detectors, signal conditioners, signal processors, memory devices, data recorders, and actuators [145]. Its purpose is to react to an input physical property (stimulus) and to convert it into an electrical signal that can be channeled, amplified, and modified by electronic devices (see Figure 2.1). The sensors output signal may be in the form of voltage, current, or charge, that may be described in terms of amplitude, polarity, frequency, phase, or digital code. This set of characteristics is called the output signal format. Therefore, a sensor has input properties and electrical output properties. The process of sensing is a particular case of information transfer and subsequently a transmission of energy.

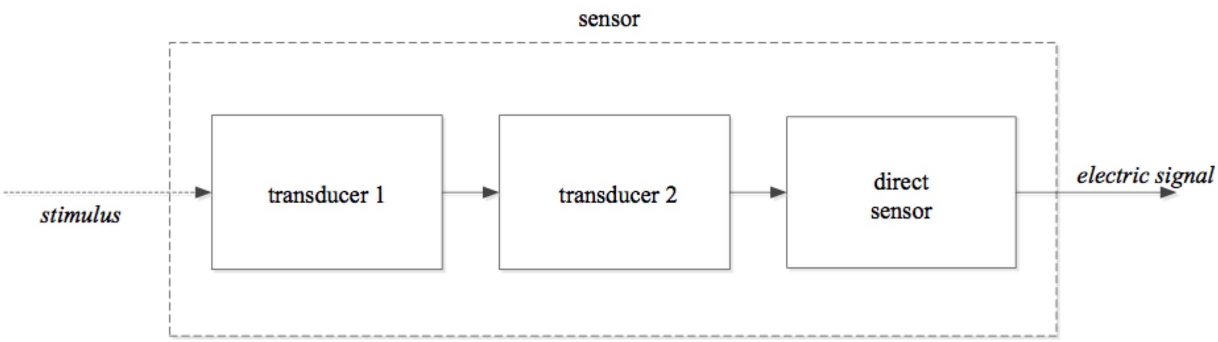

Figure 2.1: Generic sensor model.

Generally-wise there are two types of sensors: direct and complex [70]. A direct sensor converts a stimulus into an electrical signal or modifies an electrical signal by using an appropriate physical effect, whereas a complex sensor needs in addition one or more transducers of energy before a direct sensor can be employed to generate an electrical output. A sensor may be positioned at the input of a device to perceive the outside effects and to signal the system about variations in the outside stimuli. The term sensor should be distinguished from transducer. The latter is a converter of any one type of energy into another, whereas the former converts any type of energy into electrical signal.

There are several sensor classification schemes that range from very simple to complex depending on the classification purpose:

- Sensors may be of two kinds, passive and active [55]. A passive sensor does not need any additional energy source and directly generates an electric signal in response to an external stimulus. The active sensors require external power for their operation, which is called an excitation signal. That signal is modified by the sensor to produce the output signal;

- Depending on the selected reference, sensors can also be classified into absolute and relative [144]. An absolute sensor detects a stimulus in reference to an absolute physical scale that is independent of the measurement conditions, whereas a relative sensor produces a signal that relates to some special case;

Another way to look at a sensor is to consider the various physical effects which can be used for a direct conversion of stimuli into electric signals, detailed in the following section.

2.2.3.2 Sensor characteristics

Sensor faults can be dissected by exploring the transducing processes, enumerating the different methods to convert the various physical effects into electric signals, and investigating each one's advantages and limitations. This enumeration is important to this study, to understand the most basic origins of faults in sensors. The sensor material characteristics or the harshness of the environmental conditions lead to the production of a specific kind of fault. Some sensors strive to perceive an object that is moving in dusty environments while others experience issues reading a correct level observation in fluids. For instance, capacitive sensors present a considerable sensitivity and require low energy usage, making them an attractive choice for many areas. However, as pointed out by [133], the response characteristics of these sensors are very nonlinear and the offset capacitance is non-negligible and must be handled to correctly detect capacitance variations due to applied pressure and avoid errors. In summary, from a dependability perspective, it is important to distinguish sensors in terms of their operation and robustness to distinct environment conditions. When a sensor is highly sensitive but frequently faulty, a redundancy solution must be considered, possibly using a sensor with slightly less sensitivity but more reliable.

The main types of sensors according to the exploitation of displacement effects are the following [177]:

- **Resistance**. Resistive sensors, also termed as potentiometers, are based on an electromechanical instrument that transforms a mechanical variation, like a displacement, into an electrical signal capable of being monitored following conditioning;

- **Induction**. Inductive sensors are primarily based on the principles of magnetic circuits and may be categorized as self-generating or passive;

- **Capacitance**. Capacitive sensors depend on variations in capacitance in reply to physical changes. A capacitive level pointer uses the changes in the comparative permittivity among the plates;

- **Piezoelectricity**. Piezoelectric sensors quantify the electric charge created by the capacity of specific materials relative to a directly applied mechanical pressure;

- **Laser**. Laser sensors compare changes in optical path length and in the wavelength of light, which can be determined with very little uncertainty. Laser sensors achieve a high precision in the length and displacement measurements, where the precision achieved by mechanical means is not enough;

- **Ultrasonic**. These sensors use the time-of-flight method as the standard for the use of ultrasonic for monitoring purposes. A pulse of ultrasound is transmitted in a medium, reflecting when it reaches another medium, and the time from emission to recognition of the reflected pulsation is read;

- **Optical**. Optical sensors encompass a variety of parts that use light as the means to convert kinetics into electrical signals, comprising mostly on two components: a main diffraction grating, representing the measurement standard (scale); and a detection system. What is detected is the position of one regarding the other;

- **Magnetic**. A magnetic sensor is either triggered to function by a magnetic field, or by a field that defines the properties of the sensor;

In Table 2.1 a summary of the relative advantages and disadvantages of each of the described displacement effects is presented [62; 172; 177]. The goal here is not to choose the best type of sensor, but to discriminate the strong and weak points of all the types.

Beyond the limitations of the transducers, [122] explained other causes of measurements uncertainty and how only an estimation of the observed physical property can be given. When considering individual sensor measurements, the possible types of errors observed in measurement values can be classified as follows:

- **Random errors** are described by an absence of repeatability in the readings of the sensor, for instance due to measurement noise. These errors tend to happen on a permanent basis but have a stochastic nature;

- **Systematic errors** are described through consistency and repeatability in the temporal domain. There are three types of systematic errors at sensor-level:
  - **Calibration errors** result from errors in the calibration procedure, often in relation to linearization procedures;
  - **Loading errors** emerge when the intrusive nature of the sensor modifies the measurand. Along with calibration errors, loading errors are caused by internal processes;

Displacement effects	Advantages	Disadvantages
Resistance	Versatile; inexpensive; easy-to-use; precise.	Limited bandwidth; limited durability.
Induction	Robust; compact; not easily affected by external factors.	Significant part of the measurement is external, which must be well clean and calibrated.
Capacitance	Low-power consumption; non-contacting; resists shocks and intense vibrations; tolerant to high temperatures; high sensitivity over a wide temperature range.	Short sensing distance; humidity in coastal/water climates can affect sensing output; not at all selective for its target; Non-linearity problems.
Piezoelectricity	Ideal for use in low-noise measurement systems; high sensitivity; low cost; broad frequency range; exceptional linearity; excellent repeatability; small size.	Cannot be used for static measurements; high temperatures cause drop in internal resistance and sensitivity (characteristics vary with temperature).
Laser	Ideal for near real-time applications; low uncertainty and high precision in the measurements.	Weather and visual paths affect sensor when measuring distance or related variables.
Ultrasonic	Independent upon the surface color or optical reflectivity of the sensing object; excellent repeatability and sensing accuracy; response is linear with distance.	Requires a hard flat surface; not immune to loud noise; slow measurements in proximity sensors; changes in the environment affect the response; targets with low density may absorb sound energy; minimum sensing distance required.
Optical encoding	Inherently digital (which makes the interface easy for control systems); fast measurements; long durability.	Fairly complex; delicate parts; low tolerance to mechanical abuse; low tolerance to high temperatures.
Magnetic	Non-contacting; high durability; high sensitivity; small size; output is highly linear.	Very sensitive to fabrication tolerances; calibration needed after installation.

Table 2.1: Advantages and disadvantages of the various displacement effects

- **Environmental errors** emerge when the sensor experiences the surrounding environment and these influences are not considered. In contrast with the previous two types of errors, environmental errors are due to external factors;

- **Spurious readings** are non-systematic reading errors. They occur when some spurious physical occurrence leads to a measurement value that does not reflect the intended reality. For instance, a light intensity measurement in a room can provide a wrong value if obtained precisely when a picture of the room is taken and the camera flash is triggered.

In this thesis, in the design and evaluation of the proposed methodology, we consider essentially the systematic and spurious errors, which are further detailed in Section 4.2. Additionally, Chapters 5 and 6 describe our solutions to each type of errors respectively.

2.2.3.3 Sensor failure modes

The classification presented in the previous section builds essentially on the persistence and nature of the observable value errors. An alternative way to acknowledge and to deal with the fact that sensor measurements are affected by uncertainties, which is commonly used when building modular distributed systems, is to identify relevant sensor **failure modes**. Independently of the several factors leading to a sensor fault and the consequent measurement error(s), the faulty behavior of the sensor component is observed through its interface, that is, through the values it produces. Therefore, a failure mode characterizes a certain deviating behavior, abstracting its causes, and considering only the measurement values produced at the sensor interface.

The main sensor failure modes, depicted in Figure 2.2, are the following [41]:

1. **Constant or Offset failure mode**: the observations are continuously deviated from the expected value by a constant offset.

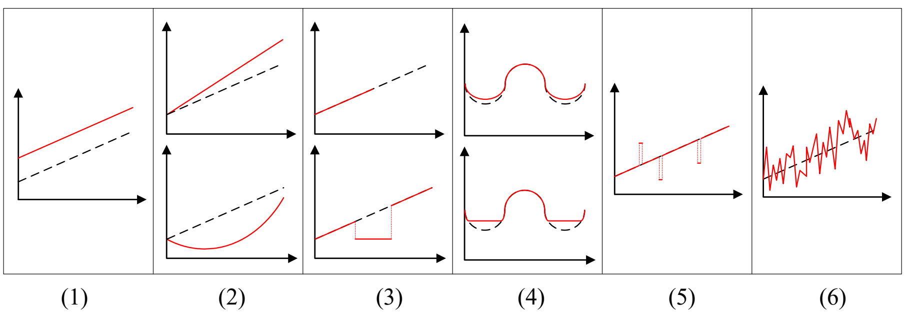

Figure 2.2: Sensors failure modes. The faulty sensor output is represented with a filled line, whereas the real values are depicted with a dashed line.

2. **Continuous Varying or Drifting failure mode**: the deviation between the observations and the expected value is continuously changing according to some continuous time-dependent function (linear or non-linear).

3. **Crash or Jammed failure mode**: the sensor stops providing any readings on its interface or gets jammed and stuck in some incorrect value.

4. **Trimming failure mode**: the observations are correct for values within some interval, but are modified for values outside that interval. Beyond the interval, the observation can be trimmed at the interval boundary, or may vary proportionally with the expected value.

5. **Outliers failure mode**: the observations occasionally deviate from the expected value, at random points in the time domain;

6. **Noise failure mode**: the observations deviate from the expected value stochastically in the value domain and permanently in the temporal domain.

Comparing this classification of sensor failure modes with the classification of sensor errors previously introduced, it is interesting to note the direct correspondence between the class of random errors and the noise failure mode, and between the class of spurious errors and the outliers failure mode. The remaining four failure modes can be seen as specializations of the systematic errors class.

2.2.3.4 Mitigation techniques

Regarding the mitigation techniques to address faults and respective value errors, a separation between what can be done at the sensor level and at higher levels is made here, namely within the application that uses the sensor data, possibly exploiting additional sources of information. Considering an individual sensor, dependability techniques can be used to prevent or tolerate the occurrence of faults and achieve an improved behavior, possibly even avoiding some failure modes. This can be described as a "basic quality improvement". Two basic techniques that are usually carried out to achieve this objective are described below: calibration and measurand reconstruction. The general approaches for improving the quality of data in WSN monitoring applications are then covered in Section 2.3.

Commonly, calibration is defined as a process under specific conditions in which predetermined known values of the measurand are given to the transducer and the corresponding outputs are recorded. In a formal way, calibration consists in defining a function $f(r, \beta)$ that, along with a set of selected device parameters $\beta \in \mathbb{R}$, will translate real sensor output r to the intended output r^*.

Typically, calibration actions are required every time a sensor is deployed in a different environment, as the physical measurement elements must be adjusted or even dedicated to the monitored device or process, providing at-start a reduction of measuring uncertainty and minimal interference with sensor functions. However, periodic calibrations are also needed to address operational conditions changes with respect to those known during the initial calibration process, which is usually performed in laboratory conditions. The lack of proper calibration can be the base cause of many errors and should hence be periodically re-done. For instance, in aquatic sensors, offset and drifting errors are often related to the accuracy range getting unbalanced, which is solvable by recalibration. This is done off-field (removing the sensor from the monitoring environment and recalibrating it in a container with water in controlled conditions), with potential data loss if no redundant way of collecting sensor data is available, and with re-deployment costs. It can also be done in-field, which is a time-consuming task on sometimes difficult conditions and, especially, exposing the calibration process to varying environmental factors that may affect the calibration accuracy.

As alternatives to manual calibration, two generic options can be considered: factory sensor calibration, with the advantage of reducing the time consumption efforts of the initial manual process, but not completely eliminating the problems mentioned before; and auto or self-calibration, enabling sensors to monitor themselves and recalibrate using a reference. This latter option, being adaptive, is potentially better to deal with varied and even unpredicted misbehaviors. It is designated as measurand reconstruction or sensor compensation.

Auto-calibration refers to methods aimed at diminishing the effect of the disturbing parameters in input/output features of sensors. Preferably, the transduced value must have a direct relation with the measurand, which should not be sensible to past information, interfering environmental factors, noise, error gain, etc. To try to compensate all these disturbances, numerical techniques have to be used. These techniques are applied after the transformed signal being quantified, through digital signal processing that must transform the sensor output signal (r^*) into a corrected value ($\hat{r^*}$).

Several auto-calibration techniques have been used with relative success, for instance exploiting statistical regression based on a priori knowledge [179] or using artificial neural networks (ANNs) [134; 146]. In the statistical regression approach the goal is to determine the polynomial approximation to the characteristics of the sensor. In the ANNs approach, the inputs are the measurements and the ideal outputs are the measurand. This model inversion is the reason why it is called measurand reconstruction. Other machine-learning algorithms have also been applied, such as Kalman Filters [37] and Support Vector Machines [81]. These choices are selected to overcome the ANNs disadvantages: neural network training may not converge to global optimum and training may need to be repeated several times, which will be prejudicial on the computational cost; and the poor generalization capabilities that may arise from insufficient data, from over or under-training, or from under or over-fitting.

2.2.4 Communication faults in WSNs

When connecting individual sensor nodes in a wireless sensor network, additional faults affecting sensor data can be introduced by the network. In this subsection the focus is on the main kinds of network faults that may affect the quality of sensor data, specifically considering faults in the time domain and faults in the value domain.

In the time domain, crash, omission or delay faults may occur. Crash faults (for instance of the radio subsystem in a sensor node) lead to permanent data absence and can only be mitigated with redundancy (e.g., a dual-radio system). Omissions correspond to sporadically missing sensor readings due to lost messages. They can be prevented by enforcing communication reliability, for instance based on message retransmission. However, reliable communication protocols are not much common in WSNs due to the additional resources (namely energy) required. Therefore, omissions do happen in sensor networks and, for the most part, they emerge because of sensor failures and packet losses. Heavy packet loss and asymmetric links occur frequently in WSNs [74; 195], for instance due to signal strength fading and intermittent or continuous environmental interference (e.g., electromagnetic). Absent values influence the outcome of any query over sensor readings. The resulting inaccuracies can be critical as in in-network processing and aggregations [110; 116; 195]. Several solutions have been suggested to tolerate these types of errors such as masking lost values through redundant information or estimating using past values [116]. Finally, delay faults are only relevant when the correctness of the application depends on the timeliness of sensor data. This is typically the case in real-time control, where the temporal validity of sensor data is bounded [107]. Sensor data becomes useless after a certain amount of time due to not reflecting the present reality with sufficient accuracy, possibly leading to system failures if used in the control process. Existing solutions to avoid timing failures are based on techniques from the real-time area, namely seizing the needed resources and using synchronized clocks to timestamp data and discard the outdated data. The existence of redundant sensor nodes can also be explored, to avoid missing important events.

In the value domain, a communication fault is translated into a message corruption [140]. However, communication protocols typically incorporate data integrity verification mechanisms that allow the detection of corrupted messages, discarding those messages and hence transforming value faults into omission faults [152]. Therefore, the only chance that received data does not correspond to what has been sent, is when some part of the communication stack in the sending or receiving node (or both) is affected by an accidental fault not covered by the integrity verification mechanisms, or when it has been intentionally corrupted. In fact, WSNs and sensor nodes can be subject to attacks that may significantly affect the quality of sensor data, among other consequences for the application. Therefore, in critical applications, it is important to deploy security techniques to avoid attacks or to mitigate their effects [49]. These security techniques are, however, outside the scope of this thesis.

2.3 Solutions for dependable data quality

Several methods have been proposed in the literature to improve the quality of sensor data. The focus here is on solutions to mitigate the negative effects of faults in data quality. The ones that are applicable at the sensor level, to mitigate data errors at the sensor interface, have already been addressed in Section 2.2.3. In this section, a discussion is presented on what can be done at sink or processing nodes. It starts by identifying and characterizing the three different forms of redundancy that may be explored for dependable data quality. They are related to the available sources of information, to which data analysis and processing techniques can be applied: a) single sensor data stream, b) multi-sensor data streams or c) multi-source data streams.

Then, and given the focus on dependability aspects, a taxonomy for dependability-oriented data quality in WSNs is presented. The relevant dimensions to reason about dependable data quality are identified, classifying the options within each of these dimensions. In this exercise, dependability-related categories are introduced, concurring to the goal of estimating the quality of sensor data. In most cases, WSN-based monitoring systems address concerns (sometimes implicitly) of improving the quality of data, but not of estimating the achieved quality. The resulting systematization underlies this study on concrete techniques for data processing, further ahead in the section.

2.3.1 Exploiting redundancy

Redundancy is a fundamental dependability technique to achieve reliability, availability and even improved performance. Therefore, WSN applications naturally exploit the existence of multiple sensor nodes and the spatial redundancy they offer. In fact, if information relative to a certain environmental process is collected through several sensors, then a range of data processing techniques to fuse the multiple data streams (from the different sensor nodes) are possible to be applied. This approach permits to obtain resulting data with more quality, masking possible faults affecting data provided by some of the nodes. In sensor networks, value redundancy [174] can be exploited to improve the quality of data. This redundancy is offered, for instance, by environmental models describing the monitored dynamic process [94] or setting limits to static or dynamic attributes of this process. Finally, if sensor data from multiple sensor nodes cannot be correlated, then a form of temporal redundancy can still be exploited. This temporal redundancy is intrinsic to continuous transmission, in a single flow, of data samples that can be correlated over time.

2.3.1.1 Spatial redundancy

The techniques aimed at exploiting spatial redundancy in WSN-based applications are known as sensor fusion techniques. Sensor fusion deals with sensor data from sensors in the same monitoring area. The sensors typically monitor a single, common, parameter, but may also monitor different parameters, which can nevertheless be correlated to infer about external conditions with simultaneous influence on them. Through processes of comparison, combination and/or smart voting schemes, it may be possible to detect faulty behaviors, erroneous information, and derive a corrected observation from the remaining (considered correct) data samples [109; 120; 198].

Sensor fusion is realised by employing a collection of techniques, such as classical Bayesian, Dempster-Shafer inference, artificial neural networks and fuzzy logic. The less mature techniques are dominated by heuristic and ad-hoc methods. The major algorithm categories and techniques are discussed in sections 2.3.2.1 and 2.3.2.2.

Sensor fusion is very useful in several situations, in particular in the following: a) when some sensors measure correctly the intended phenomena but others do not, due to failures; b) when all sensors measure correctly, but some respond to a different phenomena affecting just a subset of the sensors; c) when the data of a sensor may be masked or counter measured by other sensor but is in agreement with others; d) when one sensor may be blocked or unable to measure, but another sensor located elsewhere may have the correct data. In this case, the data from the sensor with the correct view may be combined with past information from the blocked sensor to update the overall measurements.

The authors in [40] categorize multi-sensor data fusion systems regarding to what is observed by the several sensors. Data fusion can take place:

1. **across sensors** - when several sensors observe the same variable. For instance, when the temperature of a particular object is monitored by a set of temperature sensors;

2. **across attributes** - when sensors observe several quantities related with one event. For instance, when measurements of water temperature and water conductivity are

combined to define the water salinity;

3. **across domains** - when sensors observe one specific attribute in several places. An example is when sensors in different places measure the temperature and the measured values are somehow correlated.

4. **across time** - when new readings are fused with past data. For example, historical information from a former calibration can be incorporated to make adjustments on current measurements. Note that this is a particular case that applies to systems with single sensors, which are specifically discussed ahead as a form of temporal redundancy.

Durrant-Whyte [80] provides a slightly different classification of a multi-sensor data fusion system, which partially overlaps with the previous classification. They consider that sensor fusion can be:

1. **competitive** - when every sensor conveys an autonomous reading of the same variable. The purpose of this type of fusion is to diminish the effects of uncertain and incorrect monitoring. Competitive fusion corresponds to sensor fusion across sensors, in the terminology of [40];

2. **cooperative** - when the data measured by many autonomous sensors is utilized to infer information that would not be accessible through each of the sensors. This corresponds to sensor fusion across attributes;

3. **complementary** - when sensors are not directly dependent, but might be merged with the specific goal of providing a more comprehensive view of what the network is trying to observe. Thus, complementary fusion can assist in solving the incompleteness problem. This category does not entirely match the categories by [40], it is closer to sensor fusion across attributes but the idea is not extract information but to complement it.

From the above, it is clear that data fusion can take place in many ways and for different purposes, some of which not specifically concerned with dependability issues but rather functional issues. This is the case of cooperative sensor fusion, whose objective is to derive new information rather than correcting the existing one. Nevertheless, even in this case there are opportunities for applying some dependability techniques, provided that the different measures are correlated in some way. For instance, if air temperature and pressure are correlated, then a sudden change in one of them while the other remains stable can be taken as an indication of a failure.

Unfortunately, sensor fusion is not always possible. For instance, when considering monitoring activities over a wide physical area, it may be better, or even necessary (namely for cost-effectiveness reasons) to scatter the sensors in pre-identified points according to area dynamics expertise and local knowledge, to cover the most significant events. For instance, this is often the case when monitoring water bodies, because of their typically large extension and the involved complex water dynamics. It requires expert knowledge to determine the deployment locations scattered to cover the highly variable environmental dynamics. Moreover, water monitoring usually requires costly sensors [78], which makes it infeasible to have more than one in a confined area. Exploiting sensor redundancy in these conditions is thus very complex and has large associated costs.

Even when sensor fusion can be opted as an alternative for achieving increased dependability, there are a number of technical problems that may have to be addressed. For example, when monitoring environmental processes with fast dynamics, it may be necessary that all measurements are obtained at roughly the same time [120] so that they can be correlated. However, timing aspects are hard to deal with in distributed settings. For instance, network delays or incorrect clock synchronization of sensor nodes, if not accounted for during system design, can lead to incorrect data being produced by sensor fusion algorithms or require data interpolation with associated errors. Dependable sensor fusion thus requires additional design efforts, to adapt the solution to the specific application characteristics and requirements.

2.3.1.2 Value redundancy

While sensor fusion relies on the physical (space) redundancy provided by the existence of several sensors, data fusion [43; 125] is considered as an alternative approach. It does not require physically redundant sensor nodes, but relies on the value redundancy provided by extra-information, obtained by other means. The notions of sensor fusion and (multi-sensor) data fusion are often used interchangeably. In fact, data fusion can be considered a generalization of sensor fusion, when data fusion is applied to multi-sensor data. Data fusion, in general, is related to the fusion of data, no matter its source, whereas sensor fusion (or multi-sensor data fusion) describes the use of more than one sensor in a multi-sensor system to enhance the accuracy of measured data or to handle missing data.

The process of data fusion deals with the identification, association, correlation, estimation and combination of spatially and temporal indexed data or information from numerous inputs with the specific goal of enhancing the analysis and understanding of this information. The techniques employed for data fusion are essentially the ones referred for sensor fusion, which are discussed below. However, from a dependability perspective it is important to note that data fusion opens new perspectives (in comparison to sensor fusion) regarding exploitable redundancy. In particular, two forms of value redundancy are exploitable with data fusion:

- Signal analysis or analytical redundancy: used to monitor parameters such as frequency response, signal noise, amplitude change velocity among others [180]. It is a robust approach in case of strange behavior in a controlled system. If there is a strong variability of a variable, then a sensor is categorized as faulty (or the system under monitoring has been altered). This necessarily requires some bounds to be established a priori, against which the parameters can be fused to perform the intended classification.

- Model-based redundancy: with the help of simulation/mathematical models of the dynamics of the monitored system, values can be extracted to validate the measurements. [92] was a big promoter of this type of redundancy, where the system model calculates the measured variable followed by a comparison to the sensor measurement.

One potential difficulty to apply model-based redundancy is to define relevant and accurate models. The problem becomes even more difficult when these models characterize physical processes that change over time, which is often the case when monitoring environmental systems. In the case of time-varying processes, online model resetting or model parameter adaptation techniques may be employed. Forecasting modelling techniques include simulation, estimation, and syntactic methods [104]. Simulation is used when the physical characteristics to be measured can be accurately and predictably modelled. These models can be used in all types of scenarios but most studies present examples based on terrestrial (indoor) applications [121], whereas the thematic of the work herein concentrates on the complexity of the aquatic environment (e.g. water circulation). It was for this reason that in the past, aquatic systems did not consider real-time model-based data fusion [51]. Ideally, at run-time a forecasting model represents a reference to validate the sensing data, which can also be applied for optimization and planning [56].

2.3.1.3 Temporal redundancy

In WSN applications, sensor nodes continuously send new measurements of the monitored network, typically in a periodic way, to satisfy temporal accuracy requirements of the application. This creates opportunities for exploiting the temporal redundancy that is present in the multiple measurements consecutively obtained. This redundancy is necessarily conditioned by the time interval between consecutive measurements and by the process dynamics.

The sequential measurements arriving at the sink or processing node constitute a time series to which data processing techniques can be applied with dependability objectives. In other words, if past measurements are considered historical data, then sensor fusion techniques can be applied to fuse the historical data with the current measurement. For instance, it is usual that noise reduction techniques are applied to single data streams, as a preliminary data enhancement step before any other data processing algorithms are applied. Outlier detection techniques [193] are also commonly applied to single data streams, detecting a faulty measurement when it deviates too much from the recent measurement history. Given the deviations caused by intrinsic noise and complex failure modes affecting the transducing process [65], choosing the adequate margins to achieve accurate outlier detection is usually a difficult problem. One approach to this problem is to use detection patterns rather than thresholds, applied to the incoming data stream. This approach allows to detect other phenomena, in addition or instead of outliers [200]. Interestingly, outlier detection is a problem common to several areas including network intrusion, fraud detection, performance assessment, weather forecast, among others [47].

The identification of outliers contributes to improve the data fusion processes and hence the quality of resulting data. If performed by intermediate nodes, it may also contribute to enhance the network performance by preventing the transmission of messages containing outliers (thus transforming outlier faults into omission faults, possibly a good strategy in systems with redundant information sources).

It should be noted that temporal redundancy and value redundancy strategies, as described here, can be combined with spatial redundancy in a single system.

2.3.2 A taxonomy for dependability-oriented data quality in WSNs

To help the reader understanding the main dimensions, aspects and techniques that are related to the problem of achieving data quality and dependability in WSNs, a schema is provided in Figure 2.3 with a tree-like organization of the relevant taxonomy. Note that the redundancy approaches presented earlier serve as a base for the application of the techniques described ahead.

There are three main dimensions that are relevant when addressing the problem of data quality and dependability improvement: goals to be achieved, functions to be performed and techniques to be applied.

Two distinct goals are identified:

1. improving the quality of data, which is the most common in WSN applications that aim at satisfying non-functional requirements (often not explicitly specified), like reliable or safe operation;

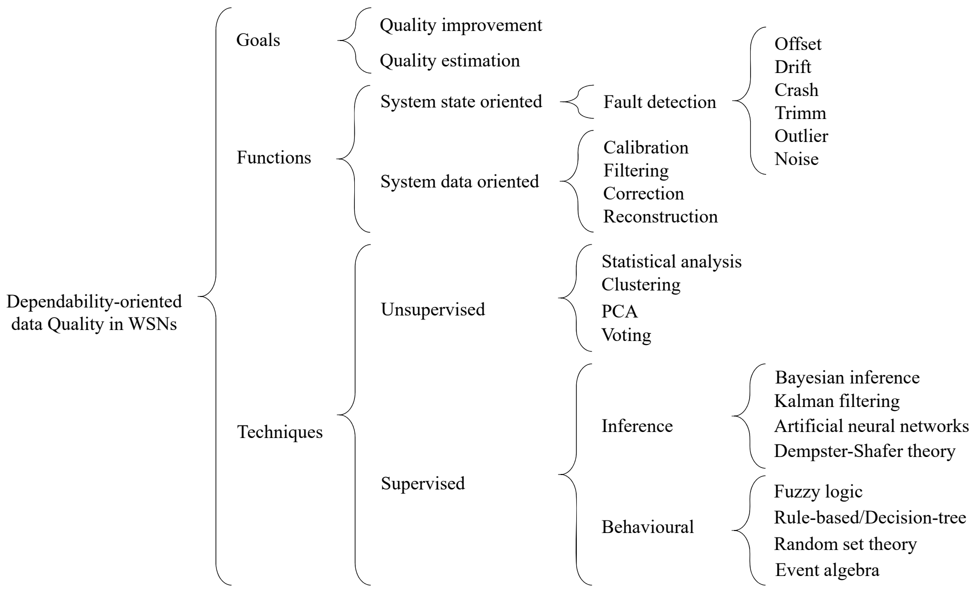

Figure 2.3: Schema of the categories of solutions for dependable WSNs.

2. estimating the quality of data to enable assessing if non-functional requirements are satisfied. Although it may not be easy to explicitly define these requirements, the advantage is that it becomes possible to define mechanisms to mitigate the negative effects of deviations from the specification. For instance, users can be notified that the application is not working properly, or the application may be stopped in a fail-safe state instead of performing some unsafe operation.

To meet these goals it is necessary to execute specific functions, which are classified in two categories: state oriented and data oriented. State oriented functions are meant to evaluate the health of system components, in particular sensors (or sensor nodes), on the assumption that this health is affected by faults. Several fault detection functions are thus considered, to deal with the different failure modes identified in Section 2.2.3. These functions are important to both improve and estimate the quality of data, respectively by providing information that allows differentiating good and bad information sources in sensor fusion processes, and by allowing to distinguish the quality of results obtained with source components in different health conditions. Data oriented functions include all those that are meant to process sensor data, namely (but not exclusively): to calibrate, filter, correct or reconstruct data affected by faults. Calibration performs an automatic adjustment of values, for instance to compensate the effect of an offset. Filtering can be used to remove outliers or noise effects. Correction allows to modify values, for instance when it is known that they are drifting from the real values or that they are trimmed. Reconstruction is helpful for instance when a value is missing, or when it is removed due to being an outlier and a replacement value needs to be produced. All these functions are meant to improve the quality of data, rather than estimating this quality. They can be combined with each other, and also with state oriented functions, for better results concerning data quality improvement.

There is a vast range of techniques and specific algorithms that may be employed to process sensor data and perform the mentioned functions. In this chapter the main ones are reviewed, providing illustrating references, and considering the two broad categories of supervised and unsupervised techniques. No matter the function to which it contributes, a supervised learning technique is characterized by a required model training and training data sets. In this category, the constructed and trained models are used in run-time to classify data, estimate new values, correct existing data, among other. On the other hand, unsupervised techniques are characterized by directly inferring the possible relations between data, without the need of a correcting model output reference.

2.3.2.1 Supervised techniques

Since data fusion is a concept that exists in works dated from the 1980s until now, many authors present data fusion taxonomies for detection, classification, and identification algorithms [85; 99; 103; 125]. These are low-level processing algorithms that can be applied in sensor nodes of a WSN. The goals here are to detect if an object is present, to classify the object and to identify it as accurately as possible.

Within the supervised techniques, the major algorithm categories are grouped in feature-based inference techniques and techniques based on behavioral models, as illustrated in the scheme of Figure 2.3.

Feature-based inference techniques achieve information mapping through classification or detection. An example is the use of statistical knowledge about an object or information about its features, as means for its identification. These techniques can be further partitioned into several classes. The following paragraphs will refer to some of the most frequently used techniques, namely parametric such as Bayesian inference, Dempster-Shafer evidential theory (DST), Kalman filters, and Artificial neural networks (ANN). It should be noted that there are many other machine learning techniques that may be of use, such as entropy-measuring techniques, pattern recognition, parametric templates, figures of merit, whose description falls out of the scope of this study (the reader is referred to [125] for further details on feature-based methods for information fusion in sensor networks).

Bayesian inference techniques use likelihood models applied to collected data to make deductions about observed quantities and even gain insights about quantities that have not been observed. Bayesian inference is used to solve the problem of efficient data gathering in sensor networks. [86] used this approach in a temperature and pressure sensor network composed with 500 nodes, to solve the problem of missing data, and to infer on that missing information. [93] used a Bayesian-network-based approach to detect global outliers in an environmental monitoring network. Bayesian inference is a computationally complex process, in which learning the classification model can be challenging, if there is a large number of correlations in the WSN.

The difficulty and uncertainty included in integrating sets of data gathered from numerous sources promoted the development of alternatives to Bayesian inference. Amid them, Dempster-Shafer theory (DST) has turned out to be one of the more considered [106; 196], for the most part because of the fundamental Dempster's combination rule [153]. The biggest benefit of this method is the simplicity of consolidating possibly contradictory evidence, independently of whether the data was directly or indirectly collected. DST adapts better to the situations than the Bayesian approach as no former probabilities must be presumed regarding the potential node behavior, and acceptance of a theory does not define rejection in the contrasting proposition, which allows handling contradictory indications quantitatively. In addition, [22] studied a DST approach to evaluate sensor nodes misbehaviors.

Kalman filtering is a well-known estimation-based approach to solve data quality problems in WSNs. One recent example [197] presents an algorithm to correct rough and missing information grounded on Kalman filtering to surpass the issue with querying faulty information and to enhance the exactness of data in a 1000 nodes WSN in a synthetic environment. Another example is presented in [24], in the context of an aquatic monitoring application, in which Kalman filtering was used with forecasting algorithms to assess the quality of the monitoring data series.

Artificial neural networks (ANN) are hardware or software systems that need a training process consisting on mapping input information to target values or classes. The conversion of this input information into the yields is executed by artificial neurons that try to imitate the complicated, nonlinear, and hugely parallel procedures that happen in natural sensory systems. ANNs have been used in WSNs for the most varied applications, many of which are related to fault-detection [36; 124; 128]. In consonance with the thematic of the work herein, [33] presented an ANN-based approach to detect disaster events through an environmental sensor network. Additionally, [27] presents another ANN-based approach to detect biofouling events (thus, fault events) in an aquatic sensor network.

The behavioral (cognitive-based) models group encompasses techniques that attempt to imitate and mechanize the decision-making procedures utilized by human analysts. These include event algebra, rule-based systems, and fuzzy logic. The latter technique is the most studied and applied, which justifies the particular attention to it.

According to [105], fuzzy set theory allows for imprecise knowledge to be mathematically treated by making it easier to represent or classify system state variable information. The use of fuzzy associative memory (also known as production rules) allows a proposition to have a membership value in a given class ranging from 0 (absolutely not belongs in the category) to 1 (absolutely belongs in the category). An expert specifies the production rules and fuzzy sets that represent the characteristics of each input and output variable. Fuzzy data fusion application to WSNs has at least as much popularity as ANN-based fusion, therefore its applications range from fault detection [100; 119; 156] to applications in industrial WSNs [54], environment [158] and aquatic-related WSNs [45].

There are some other mathematical approaches that have been developed in recent years, which include random set theory, conditional algebra, and relational event algebra [104].

Random set theory complements the existing theories of random vectors and of random functions serving as a mechanism for modelling observed phenomena. It can be applied to incorporate ambiguous evidence (e.g., natural language reports and rules), and various expert system methods into multi-sensor estimation. Conditional event algebra refers to sets with one or more finitary operations defined on it that satisfies a list of axioms, whose domain consists of logical objects using a type of probabilistic calculus suited for contingency problems such as knowledge-based rules and contingent decision making. Relational event algebra is an extension of conditional event algebra where functions of probabilities formally representing single event probabilities represent actual relational events considering appropriately determined larger probability spaces, providing a systematic basis for solving problems involving pooling of evidence.

2.3.2.2 Unsupervised techniques

There are several unsupervised data processing techniques (Figure 2.3), which serve, just like supervised techniques, to perform the needed functions in WSN-based monitoring systems, like detection, filtering or correction.

Various Statistical analysis methods can be used as unsupervised techniques for data processing. For instance, the work in [38] resorts to statistical analysis to identify events, recognize observation errors, and predict absent measurements in ecological WSNs. The proposed method requires learning statistical distributions of differences between measurements of a sensor and those of its neighbors, as well as between sequences of single-sensor measurements. According to the author, there is a large degree of spatiotemporal correlation in scalar physical variables, which provides a spectrum of oscillations between adjoining or successive readings with little differences. Based on successive readings, their distribution can be learned allowing to detect outliers when a reading value is lower than a determined threshold, in what is defined as the statistical significance test.

Clustering techniques are quite common in WSN-based applications. The general procedure is to integrate analogous information into groups with identical comportment. Data not belonging to these clusters, or belonging to a smaller cluster would be considered outliers, if this is the goal. A simple and well-known clustering algorithm is the nearest neighbor, which associates the most similar measurements. For example, the approach was used by [42] to handle unsupervised outlier detection and, in particular, to identify global-wise outliers. Every node utilizes distance similitude to locally distinguish anomalous readings and transferring those readings to the nearby nodes for confirmation. These nearby nodes will repeat this process until the entire network ultimately agrees on the overall anomalous readings. The downside of this method is the lack of scalability to large-scale networks. The most used method to measure the similarity between two data instances is the Euclidean distance. For instance, this is used in [201] in the context of target classification in a multi-channel seismic network.

The spectral decomposition-based approach aims at defining standard behaviors in the data by utilizing principal component analysis (PCA). PCA allows to decrease the magnitude of an information set in which there are many interrelated variables, while holding as much as could be expected of the variety present in the set. [48] proposed a PCA-based method to address the data integrity arising from the imprecision triggered by faulty sensor nodes. The method requires a model of the standard behavior to be built a priori, by selecting appropriate principal components (PCs), and allows the detection of outliers.

Voting methods are useful to fuse information from several sensors, particularly when applied to detection and classification declarations from multiple sensors. These declarations are treated as votes, to which majority, plurality, or decision-tree rules are applied to obtain a result that is more dependable than what would be obtained with a single sensor output [104]. This allows, for instance, masking false alarms when the sensors are used to detect the occurrence of some event, thus preventing premature reactions or countermeasures. In this sense, voting methods are also appropriate for fault-detection, to decide which node is the faulty one [21; 75]. Finally, they are used in several other application contexts, such as WSN security [113] and sensor faults in on-body sensor networks [187].

2.4 Data quality in aquatic environments monitoring

Despite the fact that any WSN deployed in an uncontrolled environment may share the same fault-related problems described previously, the focus herein is in several issues that must be considered when applying solutions for dependable data quality in aquatic sensor networks.

WSNs for all purposes have been subject of many studies, including the ones focusing on dependability of sensor nodes and related communication issues. Still, there are only a few developments and deployments of WSNs in water environments. Indeed, aquatic environments pose several challenges for WSNs, in particular in estuaries due to the large range time scales present: from small scales associated with short waves to seasonal variation associated with maritime summer and winter conditions. Tidal scales present a significant variation at semi-diurnal scales.

At the sensor level, the aquatic sensor nodes can be divided into two types of devices: floating and diving. The former operate at the water surface while diving sensors monitor the characteristics of the remaining water column. Variables being measured on both types include salinity, temperature and water quality parameters. Given the complexity of the water dynamics and the high cost of water sensors (preventing a widespread use of sensors across the whole water body), it is imperative to have a reliable aquatic WSN-based monitoring system. Several operational properties should be accounted for in the design of both floating and diving sensors in order to obtain a reliable network:

- **Power consumption** - water bodies are frequently located far from power infrastructures, making power availability a concern. The use of renewable energy devices could be a solution, but the isolated nature of most water bodies makes vandalism or theft a reality that often endangers aquatic WSNs. Therefore, battery supported low consumptions sensor are usually required;

- **Data storage and transmission** - most water sensor nodes store data in attached loggers, providing the possibility for data transmission through GSM or 4G infrastructures or through some WSN with a gateway to servers in the Internet. As power consumption is a concern, the rate at which data is transmitted must take into account the trade-off between application requirements (better temporal accuracy requires higher data rates) and the autonomy of each node (better autonomy requires lower data rates). Typically, sensor power supply should at least be sufficient to support data storage and transmission requirements during the time period between consecutive maintenance interventions;

- **Robustness** - the harsh conditions in aquatic environments make measurement failures a real concern, either by sensor clogging or data logger malfunctioning, among other factors. To prevent data losses in unforeseen crashes, data logger backup mechanisms should be envisioned.

At the network level, if terrestrial WSNs are compared with aquatic networks, it can be concluded that protocols designed for terrestrial WSNs are usually not suitable to accommodate the requirements of the aquatic environment [58; 118; 138]. Firstly, the challenges/requirements of operation of sensor networks in aquatic environments have to be considered at design stage [67; 101]. Additionally, the choices of communication protocols and techniques will depend on whether the sensor node will be operating at the water surface or along the water column. Solutions deemed as the best approaches for terrestrial sensor networks may not perform equally well in aquatic WSNs, given the effect of this medium on data transmission. So, a current challenge in protocols for the water networks is the revision of the existing algorithms to take into account the high variability of the environmental conditions, the type of sensor (floating/diving) and the communication challenges.

When addressing solutions for dependable data quality, the focus is on the redundancy issues in the water monitoring networks, namely on spatial redundancy through multiple sensors and its problems, and how to attain value redundancy:

- **Spatial redundancy** - in aquatic sensor networks, where long range communication between sensor nodes is standard and sensor nodes are quite expensive, the monitoring stations are scattered over large areas, being frequently far away from the control centre. It is improbable to have redundant sensors in a same location. Other related challenge is the selection of the type of sensors for this harsh environment and how to distribute them according to the desired application, making difficult the exploitation of spatial redundancy.

- **Value redundancy** - in aquatic monitoring networks there can be value redundancy schemes by using forecasting tools. These are composed mainly by physics based 3D modelling of the fluid dynamics that are sometimes used to force sediment or water quality models. Current forecasting systems integrate well-established numerical models of riverine, estuarine, and ocean circulation [69]. Most of the more recent models compute the three-dimensional fields of velocity, salinity and temperature and the free-surface elevation, such as ADCIRC [114], FVCOM [50], ROMS [84], SELFE [189] and derivative models (SCHISM [194]). Until recently, the restrictive computational requirements and the difficulties to combine processes occurring at different scales limited the applications that coupled high-resolution circulation and water quality models, for the simulation of the fate and transport of water quality variables (e.g. chlorophyll, ammonium, faecal bacteria, hydrocarbons). Nowadays there are some well-established coupled hydrodynamic and water quality models, such as HEM-3D [130], NEMURO [102], ROMS and ECO-SELFE, within SELFE [148; 149], used for forecast purposes [59].

The reality for the aquatic sensor networks is that the subject is widely open for research, with very few or none existing studies. Nevertheless, there are many opportunities for the use of WSNs in the water environment, as well as some already existing applications, which are reviewed here. Some of the opportunities for bringing WSNs to water environments are the following:

1. Land-based sensor networks solutions, such as those used in homeland security and military applications, can be expanded to water environments if the WSN can be applied in their harsh conditions;

2. Ocean, rivers and lakes thoughtful monitoring of the different variables of the water, coupled with climate observation, is mandatory for the characterization of water bodies and anticipation of harmful events. WSNs are an attractive alternative to conventional solutions and the availability of both surface (floating) and diving sensors cover the whole spectrum of needs. Moreover the capacity to handle data in real-time in WSNs makes them particularly fitted for the automatic validation of daily circulation forecasts;

3. The possibility of using a multitude of sensors to explore the water column dynamics and its aquatic life makes WSNs a preferential choice for biological studies. Real-time picture capturing and associated data on aquatic organisms can contribute decisively to understand the biology of water bodies. In relation to this, the opportunities brought by a multitude of sensors measuring and sampling the water column, in particular in deep water bodies such as oceans or deep lakes, may have a major impact on the study of these water bodies. Quantifying nutrient levels as well as monitoring living organisms without the very large costs of operating conventional equipment in vessels may be very relevant in aquatic research;

4. Wireless sensor networks can play a major role in improving disaster relief efforts by providing rapid and simple communication solutions. Aquatic wireless sensor networks can offer a similar solution to relief efforts of emergencies like floods, major pollution events and severe storms.

Existing applications includes CORIE, one of the first aquatic wireless sensor networks developed for the estuarine and coastal observation, described in detail in Section 2.5;

There are only a few examples of underwater sensor networks applications. The Seaweb network, integrated in the FRONT project, is a complex example of such a system. It uses the so-called "telesonar" technology [23; 53], based on acoustic telemetry and ranging advances pursued by the US Navy. The network comprises several nodes including sensors (including several oceanographic devices), gateways (using buoys that transfer data onshore) and repeaters (using acoustic modems to improve communication and relay data packets). These networks comprises many sensors and have been applied to water depths in the range of 20-60 m. The technology permits the exchange of data from the sensor to the shore and remote control from the shore to the network.

A different type of application, based on autonomous mobile platforms is described in [66]. This technology is especially appropriate for observing moving phenomena in large aquatic environments.

A more detailed review of WSN deployment in maritime environments is available in [185].

2.5 Sensor networks datasets for quality evaluation

Most of the authors and referred studies benchmark their works with own proprietary datasets from private sensor networks or through publicly available sensor networks datasets. Although in terms of data quality issues there is not a unique standard dataset to validate algorithms, it is important to define a criteria on how a dataset can be used as benchmark:

- it should be based in a real-world sensor network, ideally containing raw sensor data from multiple types of sensors in the target deployment;
- it must contain faulty sensor measurements, either naturally originated or artificially injected in later stages to mimic the intended problems in the sensors behavior;
- faulty sensor measurements must be identified (ground truth). Analogously to the previous criterium, identification and categorization of faulty measurements is mandatory whenever there is not an artificial injection of failures.

Meeting these criteria becomes really relevant when evaluating, validating and comparing techniques, especially concerning failure detection performance. With this mindset, part of this work was focused on choosing the appropriate datasets for the application of the developed techniques and methodologies. In the following subsections, an overview of the most popular public datasets based on real sensor networks is provided, which can be used to compare different approaches and datasets based on aquatic monitoring networks, considering the application of the study herein.

As mentioned, some of the presented works use private sensor networks datasets (e.g. [176] and [73]), which can not really be used as a mean of comparison or example for application. Thus, the focus is set on public access monitoring networks. These datasets are of great utility for the support of the research community in sensor networks but it is a challenge to find any that meets the aforementioned criteria, especially in what concerns the faulty sensor measurements and the ground truth supporting it. Generally all public datasets overviewed herein do not contain measurements with annotations of its accuracy or expected measurements for replacement.

In fact the absence of ground truth is actually a major problem in the evaluation of fault-detection algorithms, as researchers have to perform their own annotations, resulting in different results from the multiple methods of extracting the ground truth, consequently leading to inconsistencies in the performance metrics (such as accuracy and false positive rates).

2.5.1 Public datasets

Since there is not an unified survey for sensor networks datasets, the intention herein is to present an overview of repositories and most used datasets in the study of data quality and anomalies detection.

In terms of repositories, in [18] more than 450 datasets can be found, categorized by types of intended applications (such as classification, regression and clustering), of attributes (categorical or numerical), of content (such as text, images or time series) and source (such as life sciences, business or engineering). This repository is vast but well structured and with references to works performed with each dataset. For the particular situation of the study with time series, choices are limited with around 10 available datasets.

Another vast repository can be found in [12], with over 2500 datasets available, mostly oriented for classification algorithms evaluation. The datasets are not categorized but there is information regarding number of instances, features, classes and missing values. Among this multitude of options, 10 datasets are accessible whose origin is from real sensor networks.

An interesting collection of datasets is accessible in [1], reporting diversified content gathered in several locations, mostly real datasets, from 2013 until 2015. Though it can not be confirmed as sourced from sensor networks, there are mentions of multiple observation points and collected measurements regarding different attributes such as temperature, humidity or pressure in weather data.

Lastly, another useful repository can be found in [11], with approximately 65 available datasets for the specific application of outlier detection algorithms evaluation. Although there is a categorization according the content type, it is difficult to understand the origin of the data at first hand (navigating through the repository, more detailed information of each dataset can be found). One interesting note is the presence of a category with the annotated ground truth on the number of outliers existent in the dataset, though these are only useful for classification problems.

Although the above repositories are publicly available, the trend in most of the works (including the cited studies herein) is to make use of specific datasets regarding well characterized sensor networks. It follows a small list of the most used datasets in the literature:

- *IntelLab* [5] - it comprises data measured from 54 Mica2Dot motes with temperature, humidity and light sensors, that were deployed at Intel Berkeley Research Lab in the year 2004, between February 28^{th} and April 5^{th}. It is an indoor sensor network with almost 5 million data samples, containing a few visible data anomalies, most of which missing values.

- *SensorScope* [16] - based on an outdoor sensor network deployment that consists of weather stations with multiple sensors related with environmental settings. Time series containing variables such as temperature, humidity, solar radiation, soil moisture are available to download (more than 1 million data samples).

- *NAMOS* [7] - composed of data from 9 buoys and a boat with temperature and chlorophyll concentration sensors (fluorimeters and thermistors), deployed at several locations but more frequently at Lake Fulmor, CA, USA, for periods of a few days in the years 2005, 2006 and 2007.

- *SmartSantander* [17] - based on a large testbed deployed in the city of Santander, Spain, with around 3000 sensor devices, measuring environmental parameters as air temperature, CO, noise, light and car presence.

With so many other examples of public datasets collected through real world sensor networks [6; 19; 117], the current reality is that, for validation/comparison purposes, it is almost necessary to compare using one of the datasets mentioned above, given the required similarity in the ground truth.

In Chapter 5, the IntelLab dataset was used as a benchmark. IntelLab data is sourced from a indoor network, split by several rooms as presented in Figure 2.4. For the comparison and subsequent validation, a subset of the 54 nodes was selected, using only motes numbered 8, 9 and 10, with the measurements of temperature, humidity, and voltage information. This data was collected every 31 seconds during a smaller period of the full dataset (between February 28^{th} and March 5^{th}, 2004).

2.5.2 Aquatic monitoring datasets

Given the particular concern in this thesis, in aquatic environments monitoring, a well-known, public, online aquatic monitoring network was used as case study throughout the

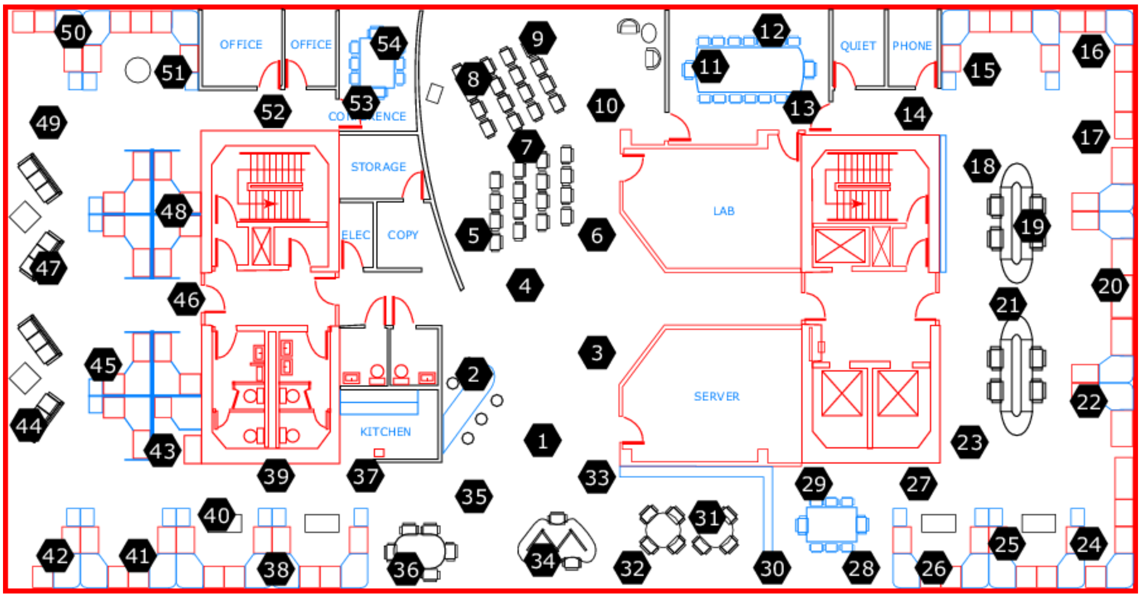

Figure 2.4: Location of the motes inside the lab.

remainder of the thesis: SATURN observation network [35]. Besides the availability of information, we selected this dataset considering the previous cooperation projects with the SATURN team. However, we list a few other aquatic monitoring networks which datasets are also available and could be used:

- *REON* [14]- River and Estuary Observatory Network provides continuous monitoring of physical, chemical, biological and atmospheric data from points in New York' Hudson, Mohawk and St. Lawrence river watersheds. The sensor network is comprised of multiple environmental sensors in floating platforms, riverbanks and underwater, measuring variables such as air and water temperature, barometric pressure, water chlorphylla-a, dissolved oxygen, pH and salinity.

- *HRECOS* [4]- Hudson River Environmental Conditions Observing System is a network of near-real-time water quality and weather monitoring stations in the Hudson River watershed. Is comprised of more than 20 stations recording every 15 minutes water parameters and weather conditions, making them immediately available to download.

- *San Francisco Bay* [20]- a network of 37 fixed sampling stations spaced apart from each other around 3 to 6 kilometers, at the riverside and deep underwater measuring the same type of parameters than previous networks. Similarly, it provides online public data query and visualization capabilities of the monitored dataset.

The case study is sourced from the SATURN network, previously named CORIE, one of the first aquatic wireless sensor networks developed for estuarine and coastal observation. The SATURN observatory [35] is deployed in the Columbia River, which forms a natural border between the Washington and Oregon states in the USA, linked to the Pacific ocean by its inlet (see Figure 2.5). This part of the Columbia river estuary is monitored by CMOP Science and Technology Center monitoring network, composed by multiple sensor nodes deployed along the river (as shown in Figure 2.6).

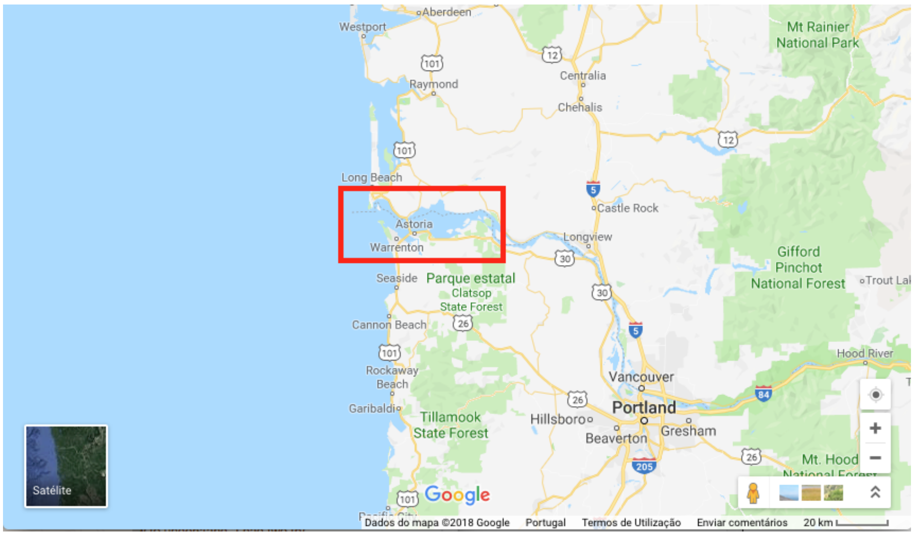

Figure 2.5: Monitored area of the SATURN network highlighted in red (image taken using Google Maps).

Figure 2.6: SATURN with highlighted stations Jetty A, Lower Sand Island light, Desdemona Sands light and Tansy Point.

This is a case of a heterogeneous sensor network deployment with freshwater stations and estuarine and plume stations that measures a suite of water and atmospheric variables.

Water variables comprise water levels, salinity and temperature as well as biogeochemistry on a 24/7 basis. This system aims at contributing to several surveillance goals, including ecological ones, such as salmon habitat evolution or the definition of the position of the estuarine turbidity maxima, and economical (hydropower management, navigation improvements). The system includes several fixed, hard-wired nodes, installed along the estuarine margins, and a wireless node, which has a drifting positioning. Transfer of data from the drifting mobile node is achieved through the fixed stations, being available to the public to assess the quality, in the Virtual Columbia River, a skill-assessed forecast modelling system of this estuary [27; 35].

SATURN also offers a human-based quality control procedure that is available for most sensors and monitoring periods, thus providing a ground truth and allowing the annotation of faulty measurements in raw data, which can be fundamental in the context of our work. In fact, this was one of the primal reasons for the adoption of this dataset as a case study.

In Chapters 3, 5 and 6, datasets from stations JettyA, Lower Sand Island light, Desdemona and Tansy Point (Figure 2.6) were selected among the available locations. The selection was based on the similarity of the nodes in terms of monitoring variables (temperature, elevation and salinity) while operating during the same periods of time and at approximate water depths. The water depth is important given the dynamics of the monitored system, since data collected at similar water depths typically allow the establishment of correlations between the measurements of each sensor.

Regarding the observed behavioral patterns, for estuarine systems, the monitored variables are greatly affected by the tides, having a variability in time according to the tidal influence (harmonic movements). Based on the tidal harmonic constituents [139], the major constituents affecting the circulation of Columbia river are M2(principal lunar semi-diurnal) and K1(lunar diurnal constituent), where M2 is the largest. The period of the M2 is about 12 hours and 25.2 minutes, corresponding exactly to half a tidal lunar day. This observation is important for the correct assimilation of the behaviors of the sensors during its monitoring process, as perceptible in Figure 2.7.

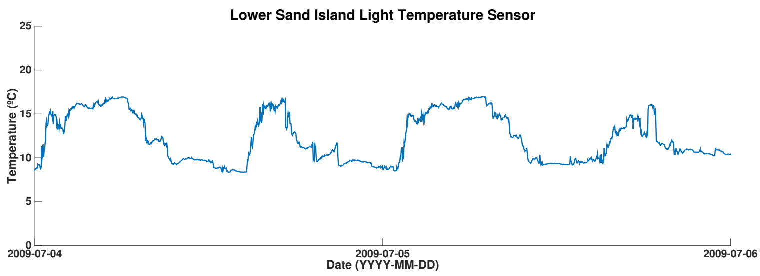

Figure 2.7: Temperature (Celsius degrees) measured for 2 days in Lower Sand Island light.

Another important observation is that throughout one calendar year the monitored variables behave differently. This behavior is related to the water dynamics in the Columbia, namely the balance between freshwater and saltwater (leading to a baroclinic circulation), and phenomena associated with atmospheric dynamics (waves, storm surges and temperature exchanges between the air and the water) (Figure ??). The involved monitoring data has thus complex seasonal (maritime winter/summer) signals, a strong contribution from the hydrographic basin (in particular over ice melting periods) and a harmonic behavior (acting at diurnal, semi-diurnal and spring/neap tides scales of approximately 15 days). Knowledge of the physical processes being monitored is important for the selection of the appropriate monitoring techniques, as well for their configuration. For instance, supervised data fusion techniques require training data sets that represent the observed physical processes as fully as possible. Therefore, by knowing that relevant changes are observed within some period, it is possible to use training data that fully covers that period.

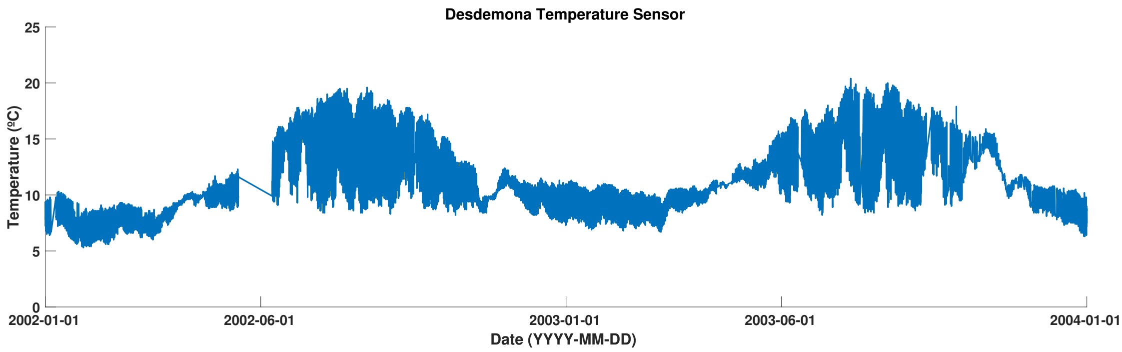

Figure 2.8: Temperature (°C) measured for 2 years in Desdemona Sands Light.

2.6 Summary

Assuring the quality of sensor data is important in WSN-based monitoring applications. In the last decade this dependability aspect has been explicitly or implicitly addressed in many works, notably by exploiting the redundancy provided by the multiple sensor nodes typically existing in a WSN. Various specific problems need to be addressed when aiming at a dependable WSN-based monitoring solution, from ensuring the reliability of the transducing process to achieving a correct interpretation of data collected from several correlated sensors.

In this chapter an encompassing perspective of the several facets of the problem was presented, focusing on dependability aspects specific to individual sensors, to the network that interconnects the sensor nodes and the processing nodes, and to the processing tasks that are performed within the processing nodes. This separation of concerns allowed to: a) clearly expose the possible causes of data quality loss from the source to the final output; b) describe specific mitigation solutions; c) provide a dependability perspective on what can be explicitly done to achieve improved data quality and assess this quality. Particular focus was given to the different forms of redundancy that may be exploited to achieve the dependability objectives: spatial, value and temporal redundancy. These are intrinsically related to the many sensor and data fusion techniques commonly employed, also portrayed in the chapter. Knowledge of the physical processes being monitored is important for the selection of the appropriate monitoring techniques, as well for their configuration. For instance, supervised data fusion techniques require training data sets that represent the observed physical processes as fully as possible. Therefore, by knowing that relevant changes are observed within some period, it is possible to use training data that fully covers that period, chosen to illustrate the multitude of options that are studied to solve directly or indirectly data quality problems. A specific outlook on data quality issues and open problems in water monitoring applications was finally given.

Chapter 3

Multi-sensor fusion

3.1 Introduction

Ideally, to reduce uncertainties or failures in a WSN, one should have a model of the sensors at stake with the respective relationship between the medium and the given response, as well as the dependency of sensor output with regard to the environmental parameters. However, such models are seldom provided mostly because the sensors do not exhibit simple responses to the environment. In fact, the environmental parameters influence the sensor behavior in a complex fashion, thus bringing the problem of obtaining accurate readings when conditions are less favorable.

Considering that it is not possible to obtain exact models of both sensors and monitored physical processes, it is challenging to detect failures and guarantee monitoring data with the required quality. A possible solution would be to use expert knowledge for a posteriori data analysis, followed by the required corrections, as mentioned in the previous chapter. However, our goal herein is to provide a solution for applications that require dependable monitoring data on a real-time basis, which is the reason that aforementioned solution is not adequate.

Therefore, we need to use data fusion techniques to solve the problem, that allow us to automatically obtain meta-information about the monitoring data and assess their quality or, for instance, provide possible correction methods. Taking this in consideration, but with the goal, in this thesis, to propose a generically applicable solution, the use of data fusion techniques must be framed within a well-defined methodology.

In this chapter we start by providing, in Section 3.2, the framework for the methodology and the data fusion techniques presented in this thesis. In particular we identify specific failure modes affecting sensor data in aquatic monitoring systems . Then, and in order to focus the work in this thesis on appropriate data fusion techniques, in Section 3.3 we present the main contribution of this chapter. It considers the early results obtained in our work, where we performed a study to compare three different data fusion techniques: Kalman filters, statistical fusion and artificial neural networks (ANNs). Finally, in Section 3.4 we complement the study by introducing another dimension considered in the methodology: the exploitation of multiple sources of redundancy and, in particular, of information provided by prediction models that may be used as virtual sensors.

3.2 Framework for a dependable monitoring methodology

In order to design a framework that automatically detects data quality issues in monitoring networks, it is important to overview sensor faults and failures that may affect negatively the overall quality, particularly in the context of aquatic environments. We present here the overview performed for this thesis.

Based on the notion that most monitoring quality issues are caused by sensor and communication faults, corresponding with the failure modes depicted in Figure 2.2, we formulated a dependable methodology sustained in a combination of the following strategies:

1. fault detection;
2. data quality characterization;
3. automatic faulty data correction.

The aquatic environments can represent a severe impact on the operations of deployed sensors within the water medium. Although understanding all possible impacts is not the focus of the present work, their identification and mitigation is part of it. In that way, a few possible sensor failures outputs were highlighted among the case study datasets, and similar datasets, for a reference of the discussed failure modes.

Natural environmental-related events are known to have a negative influence in the aquatic sensors. This influence is often verifiable in meteorological events [78], such as storms with strong winds, heavy rain and big waves affecting overall quality, either by causing total loss of the sensors or by relative sensor displacements, which commonly interferes with the intrinsic sensing processes and disturbs or invalidates the measurements. Another problem affecting the aquatic environment sensors, is the presence of marine life (biofouling) affecting both casing and sensor intake, as observable in Figure 3.1 and Figure 3.2, where attached algae and small organisms are likely to affect the sensing process and the resulting measurements.

The following dataset illustrates some of these impacts in the LNECs aquatic monitoring network of the Aveiro lagoon [78]. The time windows in the Figure 3.3 and in

Figure 3.1: Oxidation of a water quality probe caused by the harsh aquatic environment.

Figure 3.2: Algae and small organisms attached to the sensor casing.

Figure 3.4 represent the salinity sensor, shown in Figures 3.1 and 3.2, whose data quality is decreasing rapidly without human intervention. In fact, the first period represents a continuous and abnormal reduction of salinity values, identified in October 2012, caused by estuarine life growth localized inside the sensor casing. The second period of interferences, identified from January 19^{th} to January 24^{th} 2013, was caused by a powerful storm that hit the coast. On both situations, maintenance operations had to be performed at some later time to recover the sensor.

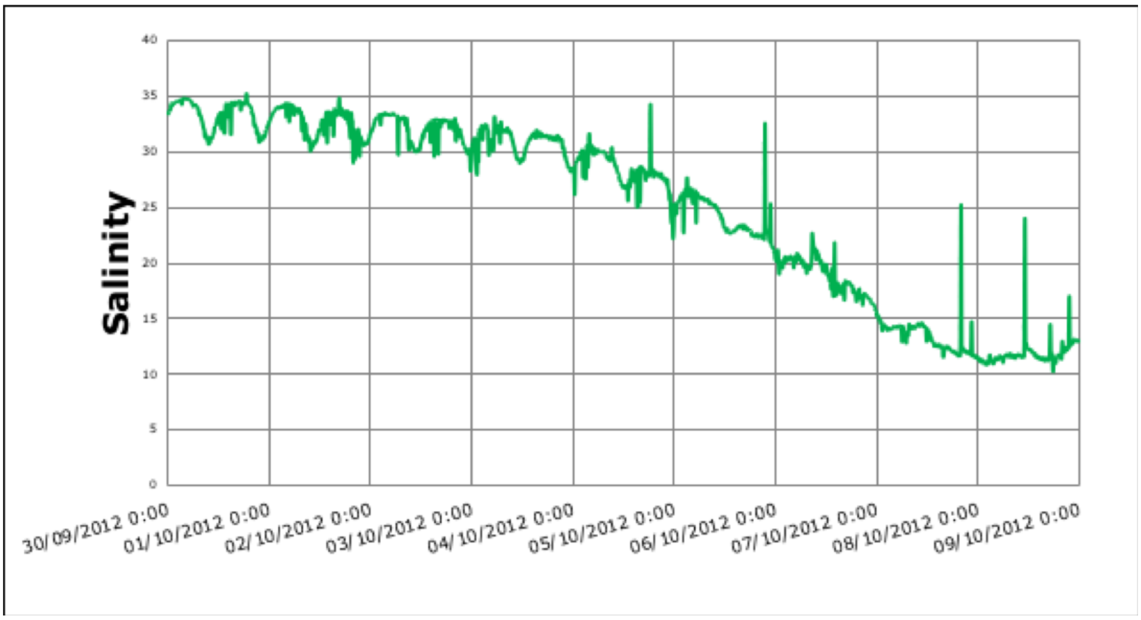

Figure 3.3: Sensor malfunction after accumulation of micro-organisms in the sensor.

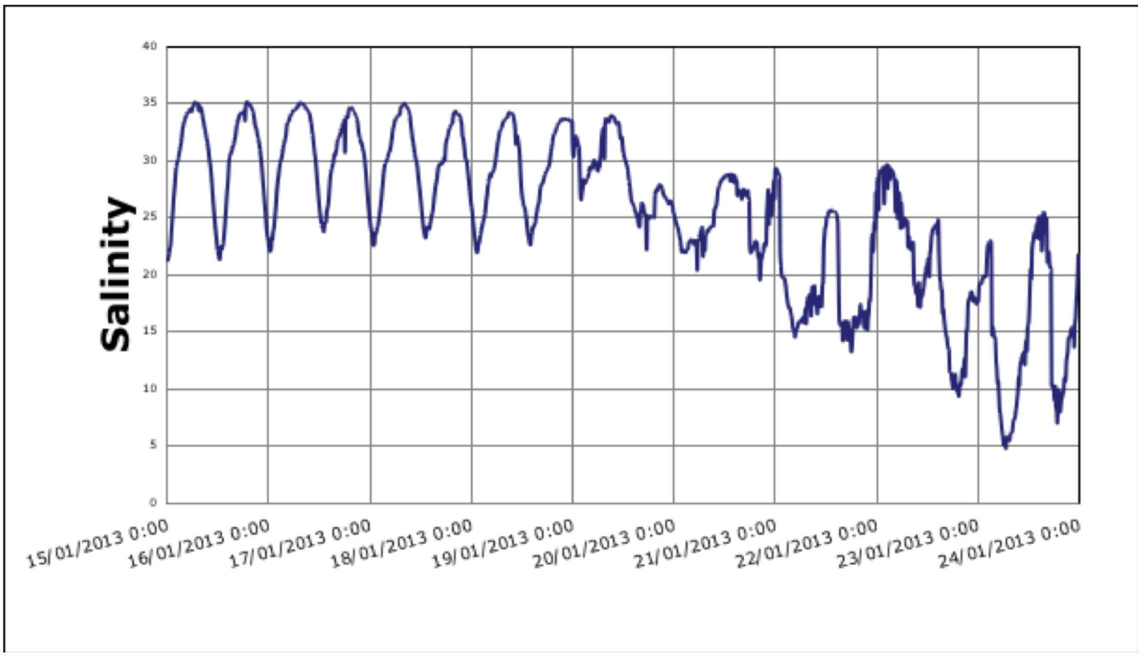

Figure 3.4: Sensor malfunction during and after a severe meteorological event.

The correspondence of each behavior to the possible failure modes may be difficult to assess in situations like the one on January 2013, when the sensor started to behave unpredictably and drifting from the initial pattern. For the October 2012 dataset the presence of noise and outliers is firstly observed followed by a drift (mixed with more outliers).

The same type of behaviors may also be observed in the dataset that we selected as a case study for this thesis work (from the SATURN network from STC CMOP). In fact, SATURN researchers have implemented a manual quality control process to detect and correct failure situations such as drifts and outliers, as observed in Figure 3.5. In this figure, taken from [15], we observe a drift pattern on a chlorophyll sensor dataset, demonstrated by the blue line (raw data). Researchers applied a running average method to estimate the drift from the expected pattern, and ultimately removed it in order to correct the faulty dataset (represented by the purple line).

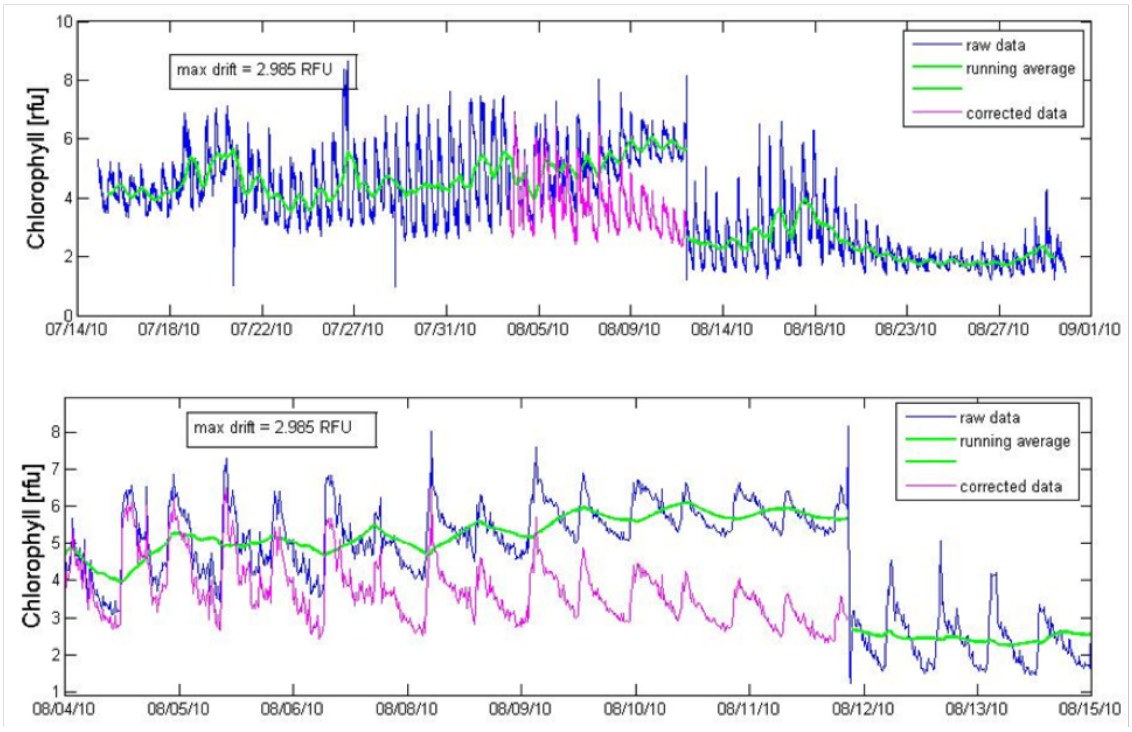

Figure 3.5: Detection and correction of drift failures in a SATURN dataset.

SATURN quality process includes an evaluation of the sensors data according to 5 levels of data quality, ranging from bad to good, where bad is considered "garbage" data or sensor malfunction, and good data is the one that have met all the defined criteria. This manual quality control procedure is performed over relevant sensor data and includes the following types of evaluation:

- Visual inspection of the data to detect periods of sensor malfunction, outliers and unusual data patterns;
- Calibration evaluation based on the results of sensor-specific field protocols;

- Corrections when existent drifts or offsets.

3.3 Comparison of data-fusion techniques

We intend to provide results to sustain the selection of an adequate technique for the further evaluation and validation of the dependable data quality methodology. Therefore, in this section, we review the techniques with a comparison among the algorithms regarding estimation errors and feasibility of the technique for the case study.

Data fusion is very diverse in techniques, features and purposes. The goal in this section is to explore a few selected data fusion techniques considering both temporal and spatial correlations between the sensors measuring in a specific area. With this in mind, three popular algorithms were selected for implementation and application to process a data set from the SATURN network. The techniques included Kalman filters, statistical data fusion and artificial neural networks. They were selected due to their widespread use for data fusion in the context of sensor networks as well as for their proven application in event detection, useful to distinguish sensor faulty situations from an environment-related natural event [24; 27; 38].

Each of the following sections overviews the respective algorithm for data fusion and how to reach an estimation of the target sensor measurement considering the neighbor sensors, followed by the respective application to the considered dataset. In all cases, the algorithms were implemented in MATLAB. The results for all data fusion estimators are mapped through signal charts, allowing the reader to verify the similarity of the resulting estimation output with the target sensor measurements, the desirable result. Given that the data fusion process usually makes use of the neighbor sensors readings, the input signals that are used in each process are also included before the respective estimation result. Lastly, in the output results, the root mean square (RMS) error between the estimation and the target measurements is provided, as a mathematical comparison measure.

3.3.1 Kalman filters

Kalman filtering has been used for many applications with the purpose of filtering data noise, estimating future states and provide non-observable states. Although associated with noise reduction, its use surpasses the typical filters for signal processing. Actually, its application as an estimator is the main use for most studies.

Kalman filtering allows to optimally estimate the variables of interest when these are hard to be measured, but an indirect measurement is available. An example of this would be estimating a temperature inside a forge from a sensor outside the forge. But Kalman filters are also used to find the best estimate of states by combining measurements from various sensors in the presence of noise. For instance, calculating the exact position of a mobile phone from a set of embedded sensors, such as GPS, accelerometer and frequency.

Regarding performance, Kalman filters are very efficient since they do not require to provide a long record of past data in order to estimate the next state, only the immediate last state and a covariance matrix is needed. Unfortunately, a Kalman filter in its basic form only produces optimal estimates for linear systems, where the system or sensor must have a linear response, which, in a real-world environment is unlikely. Therefore, as conceived originally, it is of limited use. Eventually, several adaptations of the algorithm have been developed so that it supports non-linearities, as discussed below.

Below we explain the original algorithm and how to adapt it as a sensor fusion technique for multiple sensors. The implementation of the model of the system estimated by a Kalman filter using the knowledge provided by the sensors surrounding a target sensor, with the related noise, can be written as a set of the two following discrete state equations:

1. State equation

$$x_k = Ax_{k-1} + Bu_k + w_k \tag{3.1}$$

2. Output equation

$$y_k = Cx_k + v_k \tag{3.2}$$

The variables in the equations can be read as the following: A is the state transition matrix usually defaulted to identity matrix (same length as input vector), B is the input matrix usually defaulted to zero and C is the observation matrix also defaulted to identity matrix. k is the time index. x is the vector state of system. u is the input control vector usually defaulted to zero. y is the measured output of the target sensor. And w and v are the variables representing the gaussian noise, being w the process noise and v the measurement noise.

Herein the process noise w would be the noise resulting from the target sensor or its inherent process (temperature or salinity measurement at a determined location), whereas v as the measurement noise is related to the noise in the actuators (or sensors, overall) that will be used as input to the algorithm.

Therefore, the target actuator noise can be denoted as:

$$w_{target} = \mathcal{N}(0, \sigma^2_{process}) \tag{3.3}$$

where the process noise covariance matrix is $Q = I \cdot \sigma^2_{process}$. The measurement noise v is the noise on the neighbor sensors used in the output measurement vector: $y = [measurement_{sensor_1} measurement_{sensor_2} .. measurement_{sensor_n}]^T$. Each noise is defined as:

$$\begin{aligned} v_{sensor_1} &= \mathcal{N}(0, \sigma^2_{sensor_1}) \\ v_{sensor_2} &= \mathcal{N}(0, \sigma^2_{sensor_2}) \\ &. \\ &. \\ v_{sensor_n} &= \mathcal{N}(0, \sigma^2_{sensor_n}) \end{aligned} \tag{3.4}$$

The measurement noise covariance R is defined as:

$$R = \begin{bmatrix} \sigma^2_{sensor_1} & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{sensor_2} & 0 & 0 & 0 \\ 0 & 0 & . & 0 & 0 \\ 0 & 0 & 0 & . & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{sensor_n} \end{bmatrix} \tag{3.5}$$

In state estimation problems, x is the state to be estimated, which contains all the information of the system to model. The problem is that x is not possible to be measured, hence the need to obtain it indirectly. To do so, there is y, a function of x with some noise v, that allows to extract an estimate of the next state x. The algorithm is divided into two steps:

- The prediction step, which uses a previously estimated state and the linear model to predict the value of the next state as well as the state estimate covariance:

$$\begin{aligned} \hat{x}_{k|k-1} &= A\hat{x}_{k-1} + Bu_k \\ P_{k|k-1} &= AP_{k-1}A^T + Q \end{aligned} \tag{3.6}$$

- The update step, which uses the current measurement of the output together with the statistical properties of the model, to correct the state estimate. The values calculated is the innovation covariance, the Kalman gain (K) resulting in the updated state estimate and state estimate covariance:

$$
\begin{aligned}
S_k &= CP_{k|k-1}C^T + R \\
K_k &= P_{k|k-1}C^T S_k^{-1} \\
\hat{x}_k &= A\hat{x}_{k|k-1} + K_k(y_k - C\hat{x}_{k|k-1}) \\
P_k &= (I - K_k C)P_{k|k-1}
\end{aligned}
\tag{3.7}
$$

The two steps are repeated for every sample: $k = 1, 2, \ldots, K$. Figure 3.6 illustrates the aforementioned equations and its cyclic iterations.

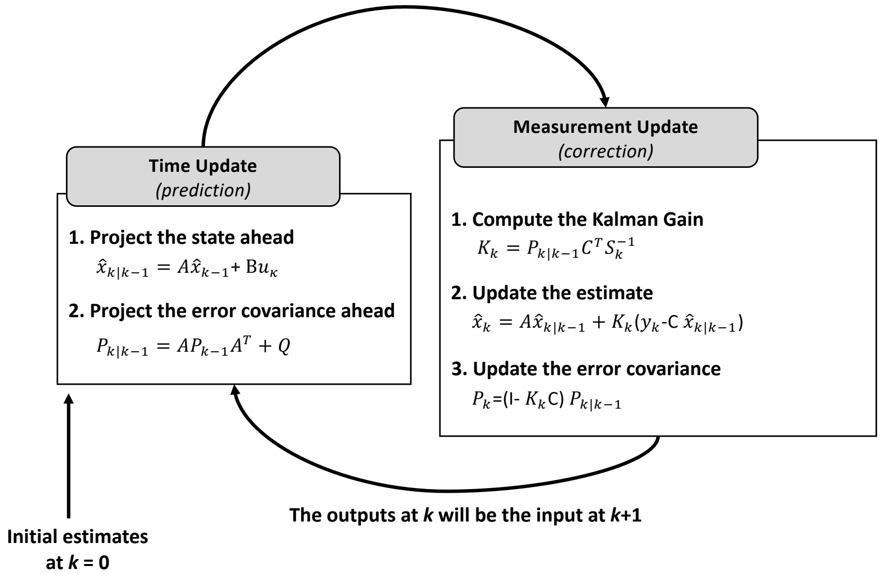

Figure 3.6: Kalman equations and iteration steps.

Besides the Kalman gain (K), $\hat{x}$ represents the estimation of x and P is the error covariance. In the measurement update step, $\hat{x}_{k|k}$ can be found as the estimate of x at time k, the main purpose of the algorithm. The covariance P is necessary for the future estimate, along with the current estimate.

For the convergence to precise outputs (estimates), a correct modeling of the system and a precise estimation of the noise is required, particularly of the measurement noise.

Again, the problem in the work herein is that it is very unlikely to have linear models in aquatic applications. Which is why using basic Kalman filter may not provide optimal results. Unfortunately, algorithms such as the extended Kalman filter (EKF), that can be applied to nonlinear systems, have limited applications and tight requirements.

This extended version transforms the nonlinear models, in each time step, into linearized equations. For instance, in a single-variable system, the equations would be composed of the current model value and its derivative. This generalization of the system (with multiple variables) is performed via a Jacobian matrix. After this linearization, the obtained equations are then worked similarly as the basic Kalman filter explained above. Alas, EKF may underperform if system state and model are not correctly guessed. In fact, many algorithms for Kalman filter in non-linearized systems are yet being developed and tested. More details on these methods can be seen in [123].

For a general setup as the required herein, the non-linearized versions are not adequate since the main requirement involves understanding the processes involved and the equations of the measurements, namely the function that will be linearized. Therefore, it follows the results of the application of the original Kalman filter focused on sensor fusion from the 3 neighbor sensors with the goal to estimate or predict the target sensor measurement.

The algorithm was implemented in MATLAB and ran for a chosen data sample of the aforementioned case study sensors, Jetty A, Lower Sand Island light, Desdemona Sands light and Tansy Point. The data sample contained information for temperature readings from all sensors from July 1^{st} 2009 to July 5^{th} 2009. The algorithm was ran for each sensor using the other 3 sensors as neighbors, during 1000 steps and for each step the readings are synchronized to the last observed reading from each sensor at the time of the target sensor reading. The results of this application are presented in the figures below. Each figure provides initially a plot of each input dataset (neighbors sensor readings) and a final plot with a comparison of the fusion outcome (displayed by the red line) against the actual sensor readings datasets. Additionally, the title of the figure presents a calculation of the root mean square (RMS) error between the aforementioned datasets.

As referred previously and observed in the results presented in Figures 3.7, 3.8, 3.9, and 3.10, the original Kalman filter is not adequate for sensor fusion in the conditions associated to the case study. The fusion result for each sensor is far from the actual readings, which can also be verified by the high root mean square error in any of the cases (always larger than 2 celsius degrees of error). These results constitute a base performance only relevant for comparison purposes.

3.3.2 Statistical fusion

In Chapter 2, the use of mathematical data fusion based on statistics was discussed in the context of the approaches for dependable data quality. In this section we consider and apply this technique to datasets taken from the same case study as considered in Section 3.3.1. We consider an algorithm for sensor fusion that was originally proposed in [38], which is based on the statistics of differences between sensor measurements. The method is presented to infer on a target sensor's next measurement based on the statistical distribution of its past readings and those of its neighbors, and also based on its own

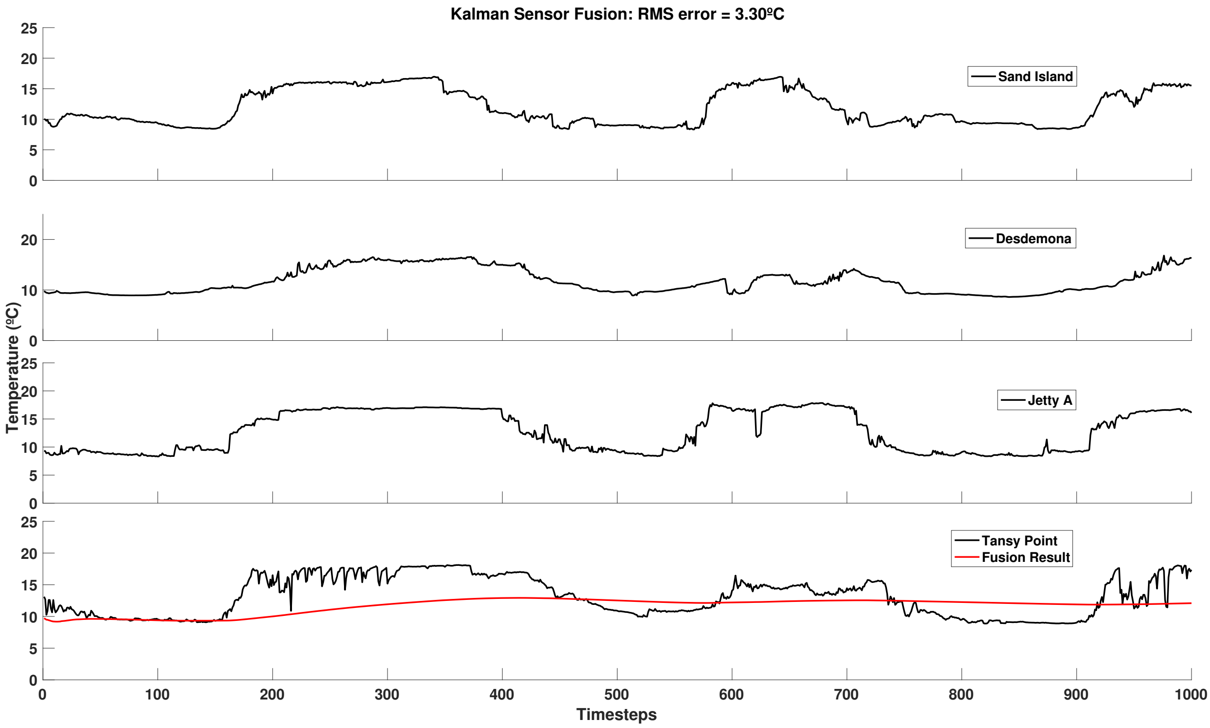

Figure 3.7: Results with sensor fusion through basic Kalman filter for Tansy Point sensor

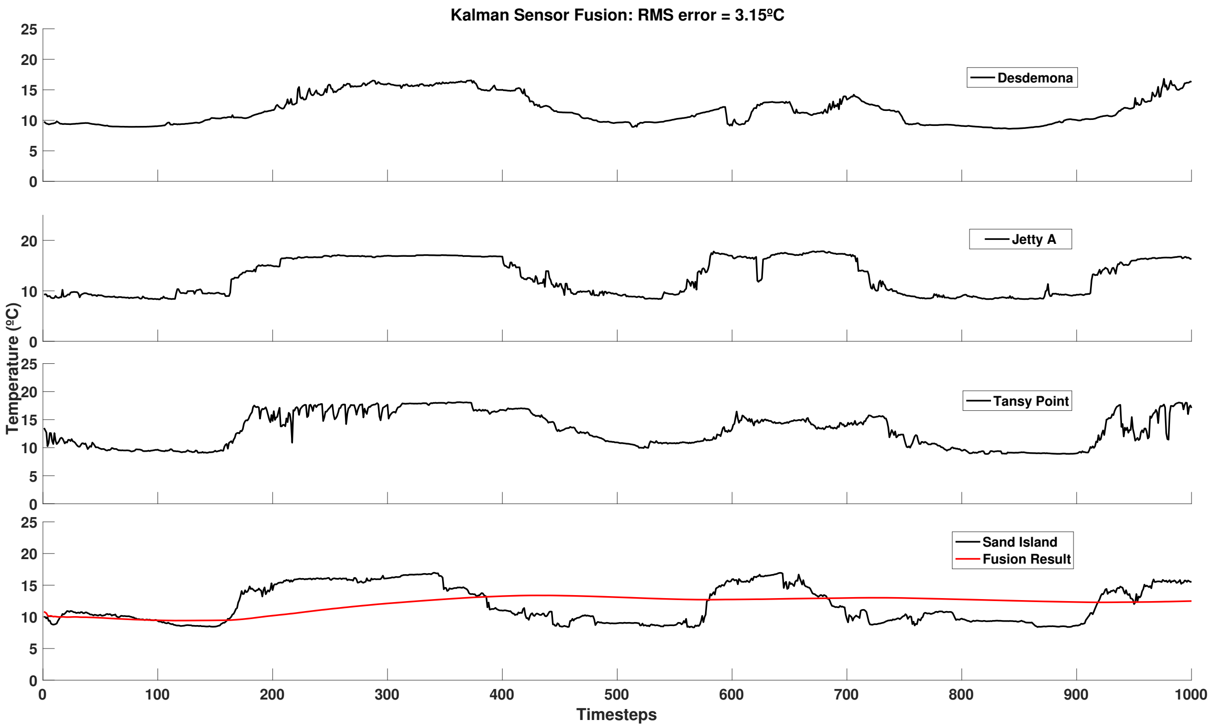

Figure 3.8: Results with sensor fusion through basic Kalman filter for Sand Island sensor

measurements at different times. This inference technique (for data fusion) addresses both spatial and temporal correlations.

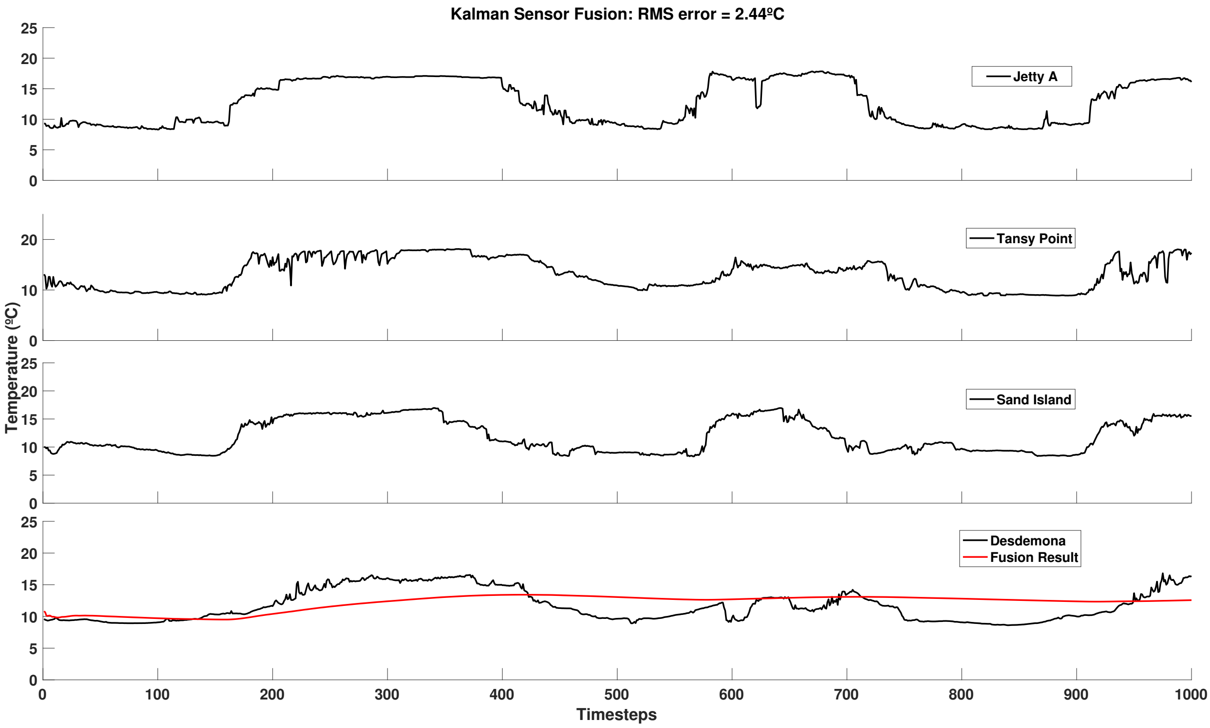

Figure 3.9: Results with sensor fusion through basic Kalman filter for Desdemona sensor

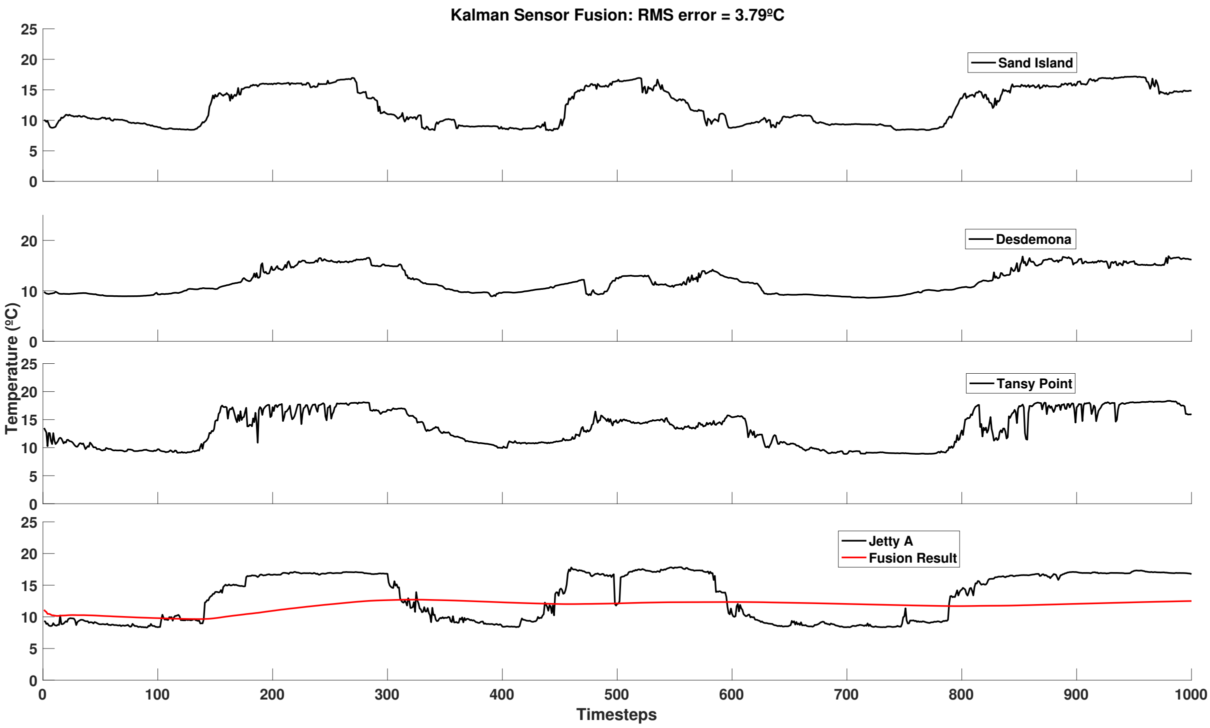

Figure 3.10: Results with sensor fusion through basic Kalman filter for Jetty A sensor

The selection of this approach for the purpose of our comparison work, was motivated by the fact that it was originally developed to be used in environmental monitoring applications [38]. The approach is well suited to learn context-related events such as climatic situations, similar to what may happen in aquatic environments. In addition, the approach is also well suited to applications involving a large amount of synoptic information and in which sensors are spread out over a large area, with distances between neighbor sensors over 100-200m.

In terms of the algorithm itself, it considers a target sensor with k neighbors. So, let ϕ be the target's measurement, ϕ_0 its previous reading and ϕ_i where $i = 1,...,k$ are the measurements of neighbors. The goal is to compute the differences between targets' current measurement and the previous one and between the current measurement and the measurement of each of the neighbors, so that $d_i = \phi - \phi_i$, $i = 0,...,k$.

As a learning algorithm, a training period is assumed to learn the probability distribution $P(d)$, from the observed differences. After this learning process, there are several ways to implement this target sensor measurement estimation by statistical inference, depending wether the distributions of the differences are known. If they are, then the training consists of estimating the corresponding parameters. If not, then methods such as frequency histograms can be used to construct the non-parametric distributions.

Exemplifying for the most common situation where the distributions of differences are well fit by known distributions, the estimator used here can be computed in terms of the learnt distributions parameters. For a normal distribution $P(d)$, that is defined by its mean (μ) and variance (σ_t^2), that can be calculated from t measurements as

$$\mu_{i,t} = \frac{1}{t}\sum_{k=1}^{t} d_{i,k} \quad , \quad \sigma_t^2 = \frac{1}{t-1}\sum_{k=1}^{t}(d_{i,k} - \mu_{i,t})^2 \tag{3.8}$$

This procedure can be optimized for sequential updates, thus allowing to minimize storage. Therefore, the equations above can be rewritten as the following, for t indexes times and $\mu_{i,0} = \sigma_{i,0}^2 = \sigma_{i,1}^2 = 0$:

$$\mu_{i,t} = \frac{(t-1)\mu_{i,t-1} + d_{i,t}}{t} \equiv \mu_{i,t-1} + K_t(d_{i,t} - \mu_{i,t-1}), \tag{3.9}$$

$$\sigma_{i,t}^2 = \frac{1}{t-1}\left[(t-2)\sigma_{i,t-1}^2 + \frac{t}{t-1}(d_{i,k} - \mu_{i,t})^2\right] \tag{3.10}$$

$$\equiv \frac{1}{1-K_t}\left[(1-2K_t)\sigma_{i,t-1}^2 + \frac{K_t}{1-K_t}(d_{i,t} - \mu_{i,t})^2\right]$$

Similarly to the Kalman filter estimator in the previous subsection, K_t is the gain factor, in which for t measurements with the maximum estimation likelihood $K_t = 1/t$.

Given the distributions parameters, it is then possible to estimate what can be the target sensor probable correct measurement. Thus the estimator for the target sensor measurement by a neighbor i is:

$$\hat{\phi}(i) = \phi_i + d_i \tag{3.11}$$

where d_i is retrieved from the distribution of differences between the two sensors. Averaging this estimation by all sensors (including the previous measurement of target sensor):

$$\hat{\phi_{av}} = \frac{1}{k+1}\sum_{i=0}^{k}(\phi_i + \mu_i) \tag{3.12}$$

where $\hat{\phi}$ is the target sensor measurement estimation and μ_i is the mean difference relative to the ith neighbor, or in the case of $i = 0$, ϕ_0 is the mean difference between the current measurement and the previous.

On the application to our case study, besides the required existence of spatial and temporal correlations between sensors, some assumptions need to be made:

1. even though sensors have different reading frequencies, we maintained a similar step for all sensors;
2. the probability density of the differences has a peak near the mean, which means that the probability of observing a difference decreases with the distance between that difference and the mean of all observed differences.

We implemented the algorithm in MATLAB using *fitdist* function for the distribution fitting. Also, for the application of the algorithm to the case study we did a few trial tests with the training period size, changing the interval size to values related with the dominant periods of the circulation of the Columbia river estuary (M2, K1, Mf periods). The minimum root mean square (RMS) error was obtained with a period of training of M2 (12 hours and 25.2 minutes), which is the strongest signal in the circulation values. Similarly to the Kalman filter application, the last readings of the neighbor sensors synchronized to the current measurement of the target sensor were used. An advantage of this algorithm, in comparison to the Kalman filtering approach, is that it uses temporal correlation by adding, as an input, the last reading of the target sensor. We present the results of this application only for the Desdemona sensor, considering that the goal is to compare with the Kalman results in the previous section, and that Desdemona sensor is representative of the other sensors in the system. Similarly to the Kalman results, Figure 3.11 presents the plots of the inputs, including now the previous readings of the target sensor, and a final plot of the comparison of the fusion result dataset against the actual readings dataset from the target sensor (Desdemona).

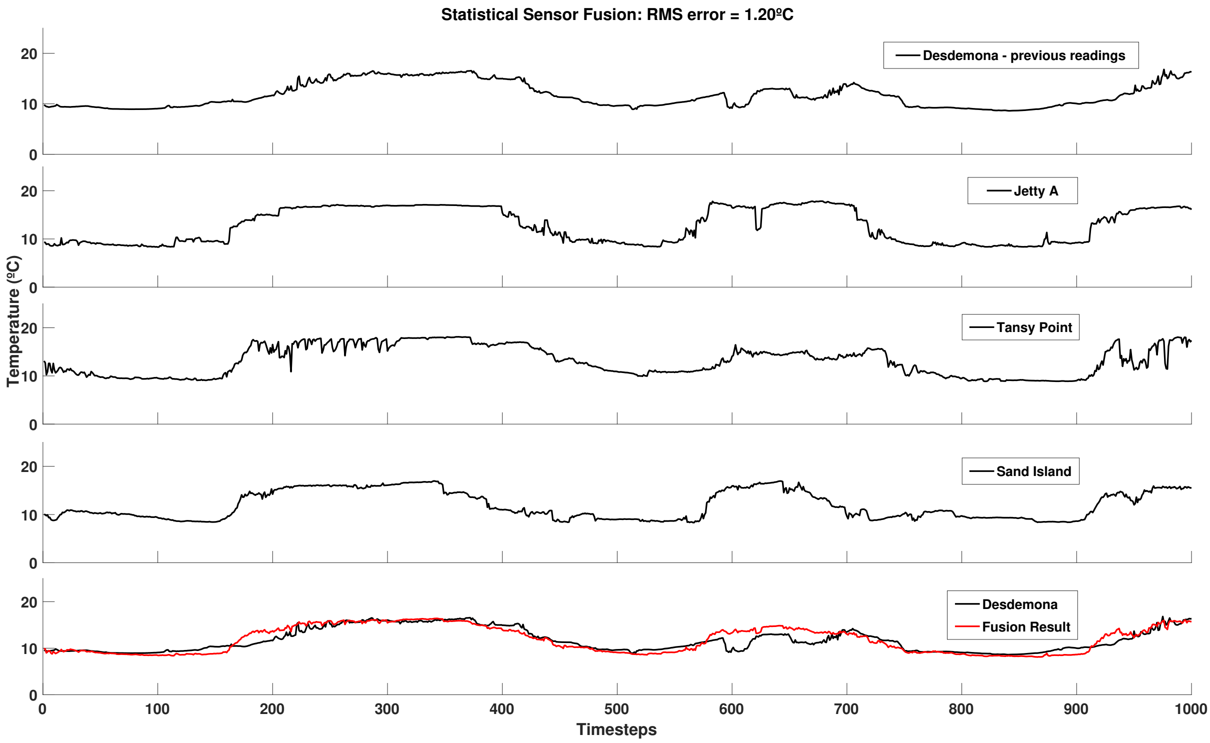

Figure 3.11: Results with sensor fusion through statistical technique for Desdemona sensor

The results in Figure 3.11 demonstrate that the use of this statistical approach as an estimator for a sensor is adequate in the context of an aquatic sensor network. Comparing to the analogous result of the Kalman filter (in Figure 3.9), we observe a clear visual improvement that is translated into a smaller root mean square error, from approximate 2.44°C to around 1.20°C. This improvement originates from two factors. First, this statistical-based technique includes a declared learning strategy, which does not happen in the Kalman filter approach. Secondly, we consider here the previous readings of the target sensor, which can be used as a trend pattern by the technique.

3.3.3 Artificial neural networks

Given that there are several ways to implement artificial neural networks (ANNs), we start by presenting the alternatives, discussing which one appears to be better for the purpose of comparing with the previous data fusion techniques, and explaining the selected algorithms in detail. Then we describe how we configured specific ANN parameters, taking into account the considered datasets to which this technique was applied for the comparison purpose. Finally, as in previous sections, we provide and discuss the results.

In Chapter 2, we described the multiple uses of ANNs specially in the most varied data-related tasks such as categorization, pattern recognition, classification and estimation, among others. In the realm of sensor fusion, ANNs can be a powerful fuser mostly due to the capability of learning models for physical processes.

Generally, ANNs consist of sets of adaptive weights composed by numerical parameters. These weights are then tuned by a learning algorithm and are capable of approximating linear and non-linear functions based on the inputs (i.e., to model non-linear systems). There are different types of ANNs but herein only feedforward neural networks are considered, which are characterized by the absence of cycles or loops between the neurons (nodes). These are considered because they are universal function approximators, in the class of linear regression models, and are adequate to represent the system in the case study.

Among the feedforward neural networks types, Multilayer perceptron (MLP) was chosen here for its ability to handle non linear problems, unlike single-layer networks. The structure of this type of ANN is presented in Figure 3.12, consisting of an input layer, one or more hidden layers, and an output layer, all interconnected by the weights (arrows) between the layers, representing the information movements from the input nodes, through the hidden layers to the output nodes.

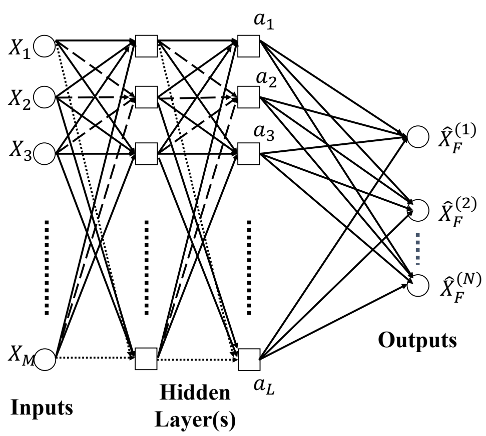

Figure 3.12: An example of a MLP feedforward neural network.

In order to perform the expected fused estimation, it is necessary to train the network. The goal is to find a set of weights and biases associated with each connection among the neural network layers (and nodes). Despite the variety of training algorithms, the backpropagation (BP) method stands out as the most used [90]. Overall, the training is carried out in a supervised manner, where the target outputs are available.

BP is based on gradient descent. The weights are initialized randomly and are updated in a iterative way to reduce the error. This error is calculated through some chosen function, such as the mean square error, applied to the current outputs of the network and the desired targets. The goal is for the ANN to learn from a set of inputs and respective outputs, which constitute the training data. Once the training process ends, the network parameters (weights and biases) are kept to be used against new inputs to obtain the fused outputs.

In MATLAB it is common to replace the BP algorithm with the optimization algorithm Levenberg-Marquardt (LM) [46]. The LM algorithm is an effective general non-linear least-squares optimization method and is used in our case study to train the ANNs for its efficiency and being considered one of the faster training methods with a good performance [97].

The process of applying ANNs to estimate a target sensor measurement follows a set of procedures that include not only the selection mentioned above but other custom steps related with the case study (or any other particular scenario). This customization begins with the features selection for the training and application (or testing).

Feature selection is the process of selecting the attributes in the dataset that are most relevant to the predictive modeling problem in question. The goal is to identify and remove irrelevant and redundant attributes from the dataset, which may in fact affect negatively the accuracy of the model. Generally, fewer attributes is desirable to reduce the complexity, thus making it simpler to understand and explain. Herein, only the readings of the temperature sensors available in the sensor nodes, already characterized in the case study (Tansy Point, Sand Island, Desdemona Sands and Jetty A), are used. As for the number of inputs (i.e. temperature readings from all sensors) different batches of tests and results are presented and explained below.

Additionally, the described ANN-based approach for sensor fusion requires the definition of the ANN parameters, namely the number of hidden layers and neurons in each layer. As stated previously, the goal herein is to model a non-linear system, thus at least one hidden layer is required. With a single hidden layer we can approximate any function that contains a continuous mapping from one finite space to another, whereas with two hidden layers, we can approximate any smooth mapping to any accuracy [126]. Additional layers will make learning complex representations feasible but also decrease overall performance. For the problem at hand, based on the accuracy requirement, we opted for 2 hidden layers in our ANN architecture [89].

As for the number of neurons in each of the hidden layers, to reach an adequate selection [96], a set of 15 dimensions were analyzed by training them for 10 testing runs per dimension. In this set of experiments, the weights and biases are randomly initialized in each run, being the random generator provided with a new seed in each testing run. Each testing run was comprised of 2000 epochs (iterations of the BP algorithm). Finally, we tested the training performance for all the dimensions, using cross-validation for the performance validation and assessment. The ANNs were trained for data fusion, considering once again a dataset from SATURN.

The performance of these trained ANNs was measured using mean square error between predictions (data fusion ANNs outputs) and targets (actual readings from SATURN dataset) from a validation data subset, that was 15% of the initial training dataset.

Given the nature of the backpropagation algorithm, the goal is not only to choose the network with the minimum mean square error (best performance), but also a good performance along the runs is verified. In Figure 3.13, the performances obtained for the set of 15 different structures (number of neurons in each of the hidden layers) are displayed. We used the Deep Learning toolbox from MATLAB to implement and train all the ANNs.

Figure 3.13: ANNs Performance heatmap: Hidden Layers Size.

Consequently, and according to the results shown in Figure 3.13, the ANN with 20 neurons on the first hidden layer and 15 neurons on the second was selected as the most adequate. This structure was then maintained for all the remaining ANNs executions in this thesis.

Considering the proposed structure, and to finalize the comparison with the previous data fusion techniques, we tested the trained ANNs with three batches of tests, promoting different features as inputs of the ANNs. We used an initial batch with 4 inputs for each data sample, representing the last readings of the 3 sensor neighbors and the previous reading of the target sensor, similarly to the application of the statistical approach evaluated in Section 3.3.2.

Regarding the two other batches of tests, we decided to explore the machine learning abilities of the ANNs, in which it is possible to perceive complex and unknown correlations between the features and the intended output. These explored abilities are explained next.

We note that more than just the last measured data point from each sensor can be fed to the ANNs. For instance, we can provide the history of measurements from each neighbor sensor. As introduced in Section 3.3.2, this history of measurements should contain enough data points to allow a complete characterization of the M2 tidal constituent, thus it should cover the past 12 hours and 25.2 minutes with respect to the target sensor reading. Additionally, as mentioned previously, in the feature selection process, we should not provide irrelevant or redundant information since it will impact the ANN accuracy and computational performance of the training algorithms. Thus, choosing the number of measurements provided in the history window (used as input for the ANNs) requires also some testing. This selection is also dependent on the sensors monitoring frequency (most of the sensors in the case study perform a measurement every 6 minutes).

Considering these aspects, the first of two other batches of tests was produced with 20 past measurements from each neighbor sensor and target sensor, corresponding to a time window of the M2 tidal constituent. Regarding the second batch, a small change was made in relation to the first batch: 60 past measurements from the target sensor were used while maintaining the same 20 past readings of the neighbor sensors.

In order to compare the ANN data fusion technique with Kalman filters and statistical fusion, we present only the results for the Desdemona sensor, similarly to what was done in Section 3.3.2. Also, to allow a direct and fair comparison, the three batches of tests were performed using the same dataset from SATURN as previously used. Figure 3.14, 3.15 and 3.16 present the results for the Desdemona sensor for each batch respectively.

A comparison with the results of the statistical approach in Figure 3.11, shows that a ANN with similar number and type of inputs produces noticeably better results regarding the RMS error. In Figure 3.14 we have an RMS error of 0.28°C, while in the statistical method the error exceeded 1.20°C. This upright improvement can be perceived as a better learning of the correlations among the network sensors, using ANNs as a data fusion technique.

Regarding the results presented in Figures 3.15 and 3.16, it reflects the aforementioned importance of the feature selection process in this context (case study). In the scenario with 20 measurements from each sensor, we can verify the accuracy increase in relation to the results presented in Figure 3.14, translated into an improvement of the RMS error

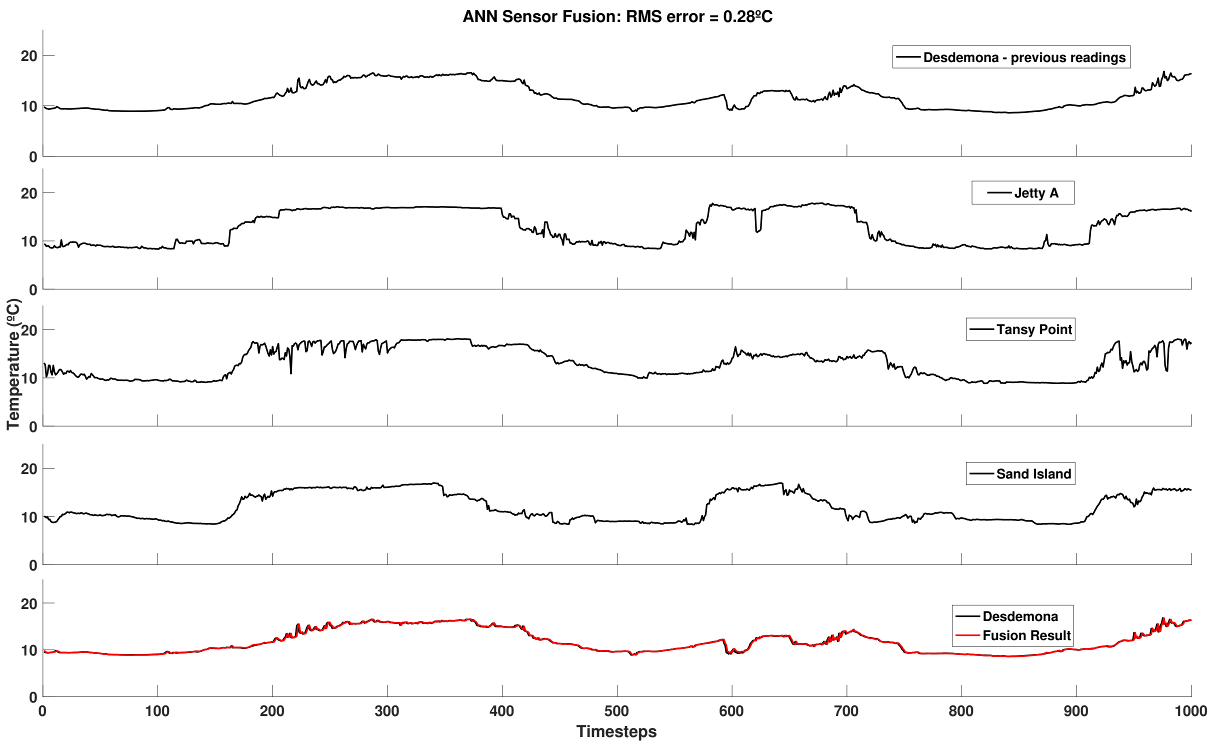

Figure 3.14: First results with sensor fusion through ANNs technique for Desdemona sensor

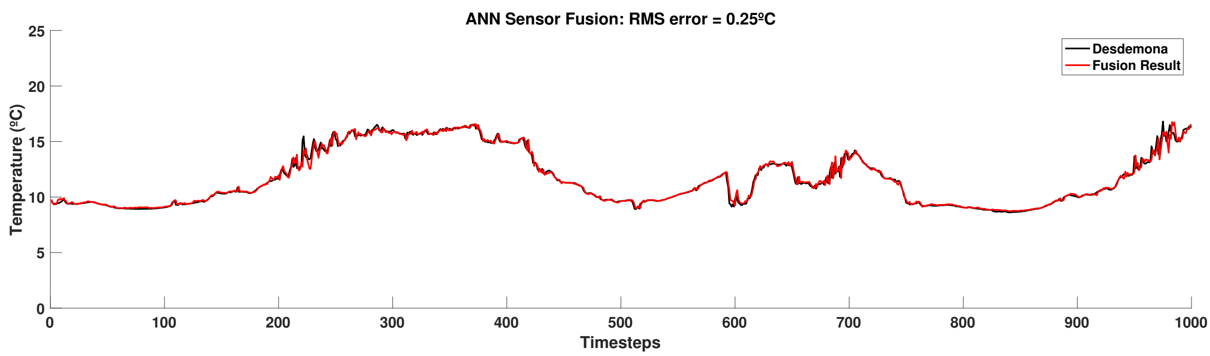

Figure 3.15: Results with sensor fusion through ANNs technique with 20 inputs from each sensor, for Desdemona sensor

to 0.25°C. This can be explained by the richer history of measurements in the inputs. However, the results presented in the third batch of tests raise the awareness over the fact that redundant information may truly hinder the ANNs performance, since we witness an accuracy decrease in relation with previous batches (both using less inputs), expressed by an RMS error of 0.42°C.

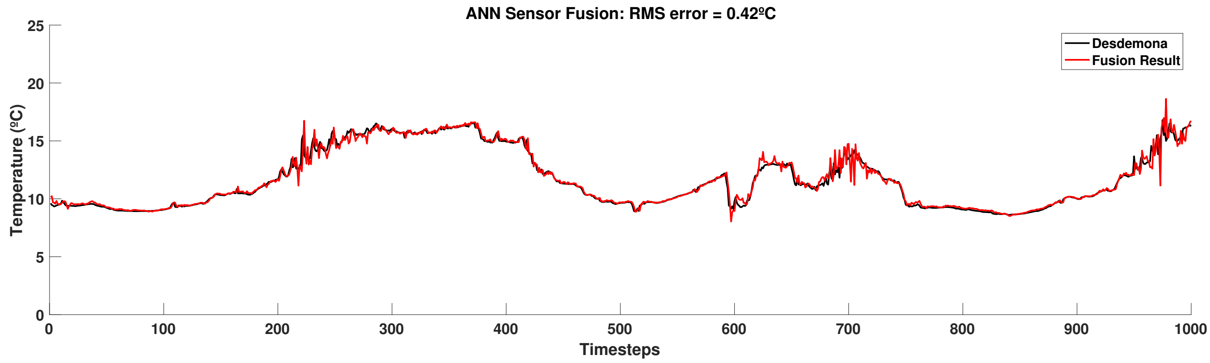

Figure 3.16: Results with sensor fusion through ANNs technique with 60 inputs from target sensor and 20 inputs from the neighbors, for Desdemona sensor

3.4 Environmental dynamics

As introduced in the previous sections, in order to effectively apply data fusion techniques we must understand the monitored environment, its dynamics and the respective existing correlations between sensors. Therefore, we present herein a discussion on how to extract knowledge from additional sources, such as environment simulation models, and how to apply it in the context of aquatic environments dependable monitoring.

These models are based in numerical modeling techniques in order to simulate the physical dynamics in the object of study. For the purpose of characterizing the quality of sensor measurements, as aimed in this thesis, these simulation methods are relevant, as they provide reasonably accurate predictions of the physical variables being measured and hence can be considered as providing a redundant source of information to be used in the fusion process.

Numerical modeling makes it possible to gather a great amount of environmental information related to a particular aquatic area on the planet. Numerical modeling of aquatic bodies requires meteorological information as forcings. This information can be obtained by meteorological data statistics or from meteorological models.

Meteorological information can be retrieved from publicly available sources providing meteorological forecasts and analysis that are suitable to impose the effects of the current (past and future also possible) weather in sensor readings. Some examples include the Global Forecast System (GFS) [3], Climate Forecast System (CFS) [2] version 2 operational model, the North American Mesoscale Forecast System (NAM) [10] or Rapid Refresh (RAP) [13], as many other weather forecast systems delivered by the National Centers for Environmental Prediction (NCEP) [8] of National Oceanic and Atmospheric and Administration (NOAA) [9].

The aquatic monitoring networks, focused in this thesis, make use of specific and complex numerical models, coupled with the results from the meteorological simulation models, to simulate the fluids dynamics of the monitored area. Such tools are composed mainly by physics-based 3D modeling of the hydrodynamics, computing free-surface elevation and the three-dimensional fields of velocity, salinity and temperature. Examples of these complex tools are SELFE [191] and its derivative model SCHISM [194], Advanced Circulation (ADCIRC) model [88; 98]; the Coastal Marine Environmental Prediction System (CMEPS) [181; 182; 183], the Eulerian Langrangian Circulation model (ELCIRC) [190], the Finite-Volume Primitive Equation Community Ocean Model (FVCOM) [178], the Princeton Ocean Model (POM) [135] or the Delft3D modeling [173].

These modeling systems integrate well-established numerical models of riverine, estuarine, and ocean circulation, allowing to use model data to extract information in order to either validate the selection of the sensors to use in the data fusion processes (Section 3.4.1), or to provide redundant information through forecast data (Section 3.4.2).

3.4.1 Model-based fusion

The process of the selection of the sensor nodes to incorporate in the sensor fusion applications becomes more relevant in complex dynamics monitoring networks, such as in the aquatic environment, due to the fact that some neighbor sensors can be less correlated or even no correlated with the target sensor due to the environment dynamics (of the involved physical processes). To illustrate this claim, we provide a concrete example by considering once again the case of sensor selection in the Columbia river from the SATURN sensor network.

Figure 3.17 represents water velocity patterns in the Columbia river and estuary, where each pattern is represented using a different color. Pink and orange colors near the mouth of the river indicate higher velocities, while dark and light blue colors mean lower velocities. Interestingly, in some areas the transition is very drastic, which means that two sensors located close to each other may end up providing quite different and non-correlated information, depending on their exact location. For instance, looking at the Saturn07, Jetty A and Sand Island nodes, in Figure 3.18, respectively marked with green, red and pink markers in the figure, one can observe that water velocity data collected from the former can hardly be correlated with data collected from the two latter (see Figure 3.19).

3.4.2 Virtual sensors

Another type of products or outputs of the referred environment models are forecasts time series for multiple parameters, including temperature or salinity, at any geographical point of the scoped area of the numerical model.

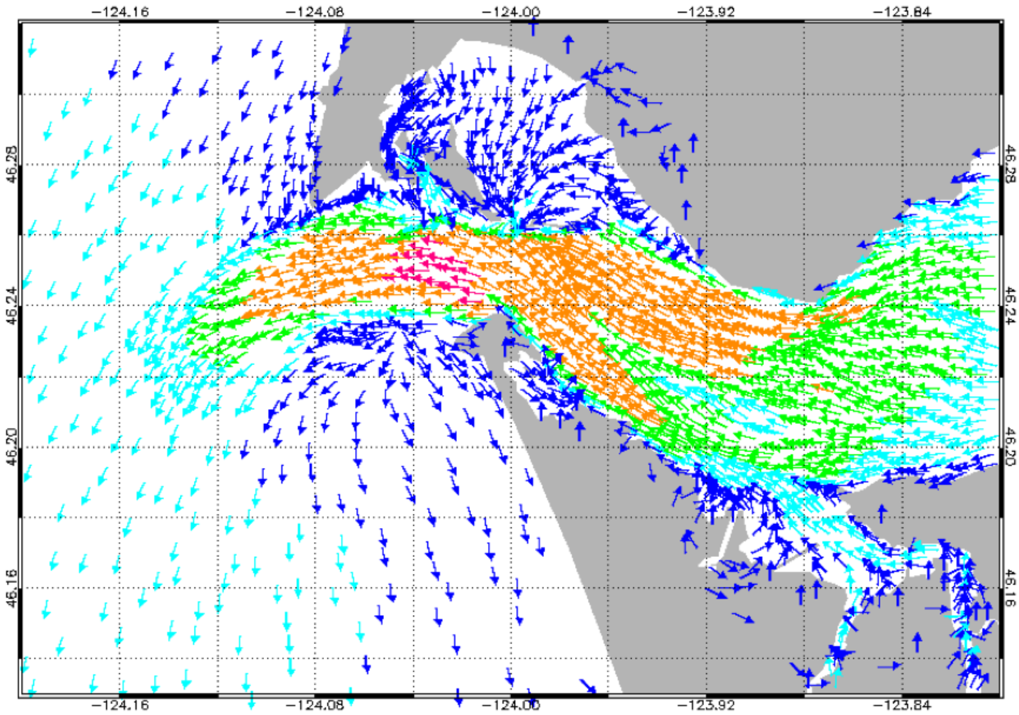

Figure 3.17: Hydrodynamics circulation outputs at Columbia River in the area of the case study sensor nodes.

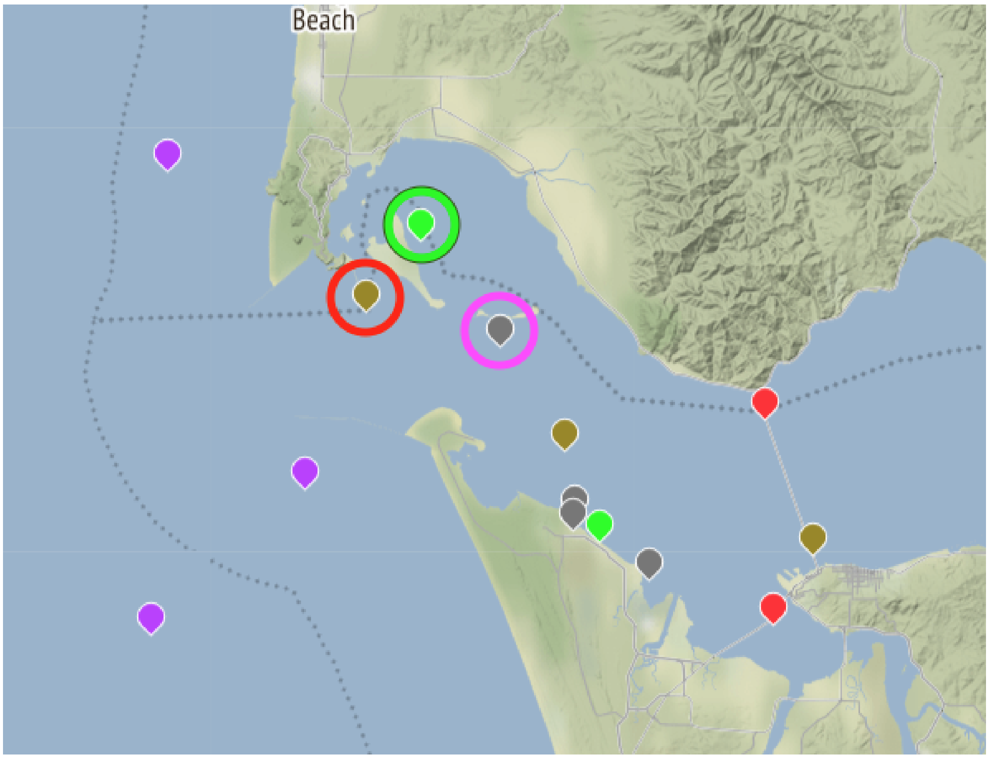

Figure 3.18: Jetty A sensor in the red circle, Saturn07 in the green circle and Sand Island sensor in the pink circle.

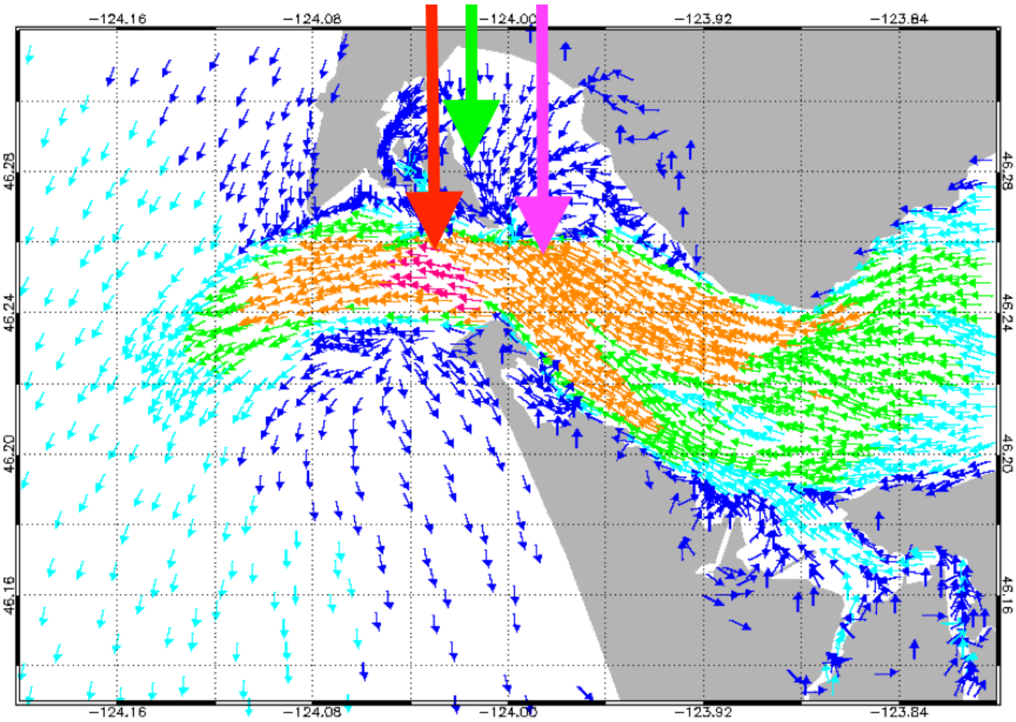

Figure 3.19: Hydrodynamics circulation outputs at Columbia River with the location of the sensor nodes.

Depending on the model parameters or stakeholders requirements, forecast information can be obtainable typically for periods of up to 48 hours comprising the current day and the next one, thus being available at the time of processing when the sensor fusion systems need it. So, if necessary by any constraint or requirement, such as absence of information from a neighbor sensor node, or simply to exploit the availability of an additional source of correlated data to increase the sensor fusion accuracy, these types of model outputs can be used as virtual sensors in the fusion process to achieve a more dependable monitoring system. The virtual sensors provide a new source of redundancy in the sensor fusion process, allowing to mitigate errors in the real sensors measurements. On the downside, these simulation models may not consider all existing processes with influence on the environment, and provide data that are limited by the accuracy of the underlying numerical methods which can cause significant errors depending on the accuracy of the numerical scheme and the model application setup.

For the purpose of illustrating the applicability of virtual sensors, we consider again the SATURN case study and the ANNs for sensor fusion, trained with the targets' sensor with 20 previous inputs and 20 from each neighbor. Following the demonstration in Section 3.3, we maintained Desdemona as the target sensor, allowing us to compare the results from the present analysis with the results provided in Figure 3.15. As virtual sensors, we used CMOP's information system to retrieve from its simulation model (based on the

SELFE [191] model) the temperature datasets for the exact location of the 4 case study sensors, for the time interval from July 1^{st} 2009 to July 5^{th} 2009, as used previously.

Given that it is possible to extract model datasets for any location in the monitored environment, we could consider various scenarios for the use of virtual sensors. Therefore, we created the following two scenarios:

1. Substitution of the Jetty A temperature sensor, which has a relatively high correlation with the target, with a virtual sensor located in the location of Jetty A, using the simulation model dataset. The objective of considering this scenario is to check if a virtual sensor can successfully replace a real one by preserving the sensor fusion accuracy;

2. Removal of the Jetty A temperature sensor from the fusion datasets. Thus, the sensor fusion process only includes information from the target sensor previous readings and the remaining two neighbor sensors (Sand Island and Tansy Point). The results obtained in this scenario can be compared with the results obtained in the previous one, allowing to conclude about the relevance of using a virtual sensor, which provides some information, instead of not using it and performing the fusion with less information.

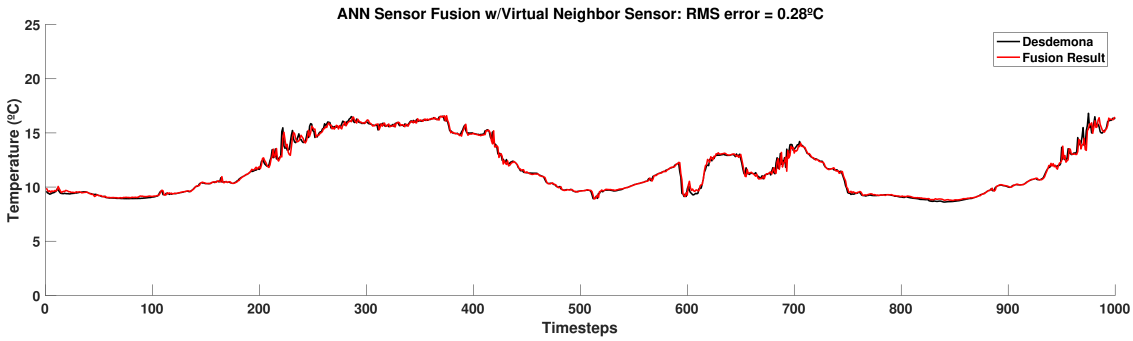

Figure 3.20: Results with sensor fusion through ANNs technique with 20 inputs from Desdemona sensor and 20 inputs from the neighbors, including a virtual sensor instead of Jetty A sensor.

Figure 3.20 presents the fusion results for the first scenario that includes the virtual sensor node. It is possible to observe that when using the virtual sensor, the RMS error was about 0.27°C. Comparing with the accuracy obtained when using the real sensor, about 0.25°C as shown in Figure 3.15, the conclusion is that including the virtual sensor does not improve the final results but provides similar results.

Figure 3.21 presents the ANN fusion results for the second scenario. In this case we can observe that the RMS error was approximately 0.32°C, which is higher than the

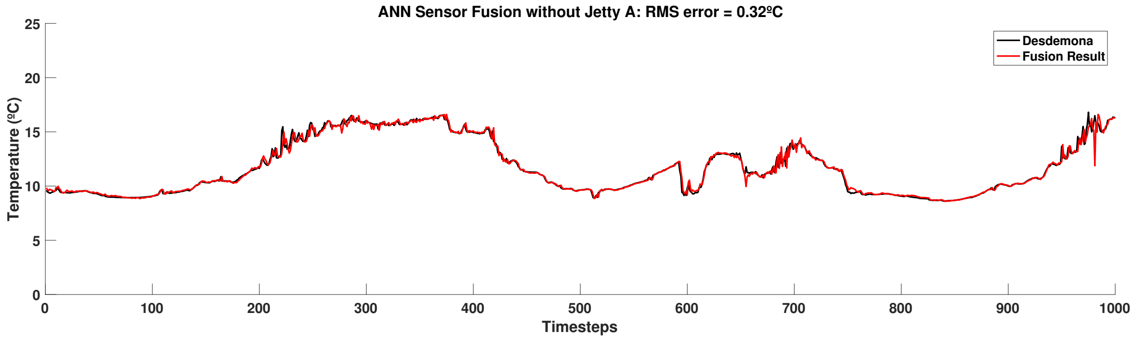

Figure 3.21: Results with sensor fusion through ANNs technique with 20 inputs from Desdemona sensor and 20 inputs from the neighbors, excluding the Jetty A sensor.

0.25°C error that was observed in the scenario in which the Jetty A sensor was present (Figure 3.15). This allows to conclude that using a virtual sensor is better than not using it. Thus, a virtual sensor still provides very useful information that can be used to replace a real sensor in case of failure of the latter. In summary, virtual sensors are a useful source of redundancy, proving their usefulness in the sensor fusion process and as a guarantee of the quality of a monitoring network.

3.5 Summary

Multi-sensor fusion is a widely discussed subject due to its importance in so many areas, from medical to aeronautics. But in all of those areas, many decisions have to be made in order to obtain reliable monitoring networks and for data fusion to be successfully applied.

The importance of the context information in the aquatic environments was discussed in this chapter. Weather conditions and the presence of aquatic life may affect significantly the behavior of sensors in the water, thus they need to be accounted for when creating solutions for dependable quality in aquatic monitoring networks. Additionally, these solutions need to be able to use the correlated information between the multiple sensors to really distinguish true phenomena resembling a sensor failure from a real sensor failure.

An overview of three popular techniques for sensor fusion, Kalman filter, statistical fusion and ANNs was presented. For each, we provided a demonstration on how to use it for sensor fusion, using the neighbors sensor data. Based on each results, we compared their accuracy (RMS error) and feasibility for generic aquatic monitoring setups, in order to decide which is the best technique for the thesis works. Considering the provided results for the three techniques, we can conclude that the ANNs are the most adequate for the sensor fusion application to the case study. Therefore, we use it extensively in the following chapters.

Lastly, considering the importance of a dependable monitoring system, we find it relevant to characterize the impact of sensor correlation in the overall monitoring data quality. The provision of simulation models outputs may support the selection of sensor nodes that are more likely to be correlated. Also, we consider the use of virtual sensors as an additional correlation source, allowing to mitigate potential physical sensors failures. For example, we can use virtual sensors as a feasible replacement of crashed sensor node.

Chapter 4

Dependable data quality oriented methodology

4.1 Introduction

Sensor measurements may exhibit errors due to sensor malfunctioning or other faults, either outliers, temporary disturbances or systematic deviations. These errors can ultimately contribute to false warnings being issued or to backing wrong decisions. This chapter is focused on a methodology to detect and identify sensor faults in environmental monitoring systems based on WSNs.

Although the goal of fault detection in WSNs is a well-known subject for the research community, many studies perform their experiments in simulation environments or controlled environment setups, where sensors represent a reliable window to the monitored system and the notion of continuous time and values of measurand meet a discrete model of time and discrete estimation of the real data. Also, many of the state-of-the-art techniques for fault detection are not meant to be applied in run-time [87] or do not consider the presence of environmental interference events on sensor measurements [63].

In this thesis, the proposed solutions to increase data quality in monitoring networks were designed by considering the need to include the analysis of sensor failures and its probable cause, the need to automatically correct the sensors measurements to compensate for each disturbance and to take into account expert knowledge about the involved environment, particularly regarding the impacting dynamics of the monitored medium.

This chapter provides a novel methodology generically applicable to monitoring systems subject to harsh and highly dynamic environmental conditions, based on data fusion techniques to explore spatiotemporal correlations between the sensor network nodes. Before describing the methodology, we discuss in Section 4.2 a set of issues with relevance and implications to the definition of the proposed methodology for dependable monitoring. These issues also have implications to the development of the specific techniques for failure detection described in Chapter 5 and Chapter 6.

In Section 4.3 we describe the building blocks of the proposed methodology. We start with the workflow and how it enables the detection of sensor faults affecting sensor measurements, how it outputs a quality coefficient for each measurement, and, if the quality is below a defined threshold, how it provides a corrected measurement.

4.2 Problem decomposition

In the previous chapters, we introduced several relevant aspects of a dependable data quality monitoring, given their particular significance in the proposed methodology definition and design.

A first aspect is the distinction between spurious and systematic failure modes. Even though the methodology encompasses both scenarios, we may need different failure detection and correction mechanisms according to each situation. We approach this differentiation with the necessity of checking not only if a sensor measurement is out of context from what the other network sensors are measuring, but also measuring a history of the sensor measurements.

Another relevant aspect is the need to distinguish true sensor failures from the false positives, which can be due to natural phenomena (events). Therefore, we characterize and define these phenomena in the context of the environment monitoring network, where it may affect the sensor measurements of multiple sensors.

Lastly, a third aspect is the use of machine learning to model sensors and its importance in the failure detection. Although we already concluded that supervised techniques allow us to estimate expected sensors measurements with a reasonable accuracy, the methodology also considers unsupervised techniques. These are typically targeted for classification purposes, which can support in true categorization of the failure modes.

4.2.1 Spurious and systematic errors

In aquatic environments, the aftermath of natural phenomena may impact the deployed sensor nodes into failure situations as proven in Section 3.2, which include not only the spurious types as absence of measurements or outliers but also the systematic failure scenarios of drifting or offsets.

Therefore, in this thesis, we focus both on sensor spurious and systematic errors, only excluding the noise errors. The proposed methodology targets generically all types of errors, but the different aspects of spurious and systematic errors are dealt separately in the respective specific implementations presented in chapters 5 and 6. The goal here is to characterize both types and introduce their specific challenges for the definition of the detection and correction mechanisms.

The categorization of the failure modes, presented in Section 2.2.3, was based on the frequency and continuity of the failure occurrence and on the observable pattern that the failures leave on the data signal. While failure modes producing absence of measurements and outliers can be placed under the spurious category, failure modes leading to offsets, drifts, jammed and trimmed signals belong to a systematic category.

All the failure modes pictured in Figure 2.2 may be described through mathematical expressions, which can be used in the definition of failure detection techniques.

Although all failure modes can be mathematically represented, the nature of the errors, spurious or systematic, associated with them, have different implications on the way the fault detection techniques can be defined. This is why we consider separately these errors, focusing on spurious errors and the respective failure detection techniques in Chapter 5 and systematical errors in Chapter 6. Furthermore, because in these chapters we focus specifically on outliers, drifts and offsets, we present herein the equations that represent the failure modes, which will be needed there.

Considering S a time series of sensor s measurements not containing any fault, an *outlier* failure is usually associated with a "random" distribution and "random" intensity. So, considering δ_k a random intensity (it can be negative) for a random index k in the time series S, the outlier o_k in that index is noted as:

$$o_k = S_k + \delta_k \tag{4.1}$$

A *drift* failure can be modeled using, for instance a polynomial expression [60]. The polynomial consists of a number of coefficients a and a number of variables $k_0, \ldots, k_n$ for every k from $k = 0, \ldots, n$, with the summation of their products forming the polynomial model. A drifting behavior is denoted during a time interval from indexes $k = 0, \ldots, n$ in the time series S. So drifted values d_k of sensor s can be represented as:

$$d_k = S_k + \sum_{i=0}^{k} a_i k_i \tag{4.2}$$

Lastly, an *offset* failure can be defined as an interval of measurements that display some offset with almost no variance to the expected value. Similarly to the previous failure mode, it is a behavior shown during a time interval from indexes $k_0, \ldots, k_n$ in the time series S, but it is characterized by an offset value e added to the expected measurement, plus an almost negligible variation with intensity i. The biased or offset values b_k of sensor

s for every k in $k_0, \ldots, k_n$ can then be represented as:

$$b_k = S_k + e + \mathcal{N}(0,1) * i_k \tag{4.3}$$

In monitoring networks, solutions for failure detection and mitigation need to aim not only to the more popular spurious failures as the outliers, but also the less frequent scenarios of offsets and drifts.

Although it is recognized that failure detection solutions depend on the type of errors being considered, for the purpose of defining a generic methodology this distinction can be omitted. What is important is that failure detection is recognized as necessary, whatever the concrete failure modes being considered and failure detection mechanisms being implemented.

4.2.2 Failures and events

It is important to distinguish the sensor faults from the environment-related events. These events can be perceived by the fault detection mechanisms as failures, which in this case are indeed false positives. To avoid this problem we start by defining both events and failures as we comprehend them in this thesis.

We characterize events in this thesis as the physical phenomena that impacts the monitored environment to some extent. These can be, for instance, lightnings or earthquakes, which are typically short duration. But events can also be long lived like for instance heavy rain or incrustation of marine life in the sensors. All such events are unpredictable or almost random, and may affect the sensors measurements. We consider that an event has a wide scope and it is not a localized happening. For instance, an object collision with a sensor is a short-lived happening that may produce a sensor fault (possibly causing an outlier). The presence of animals in contact with or near a sensor is an example of a long-lived fault (in this case possibly causing an offset error).

Our objective is to detect faults. However, events may lead to deviations from expected values in measurements that may be wrongly perceived as faults. We want to distinguish between events and faults. Therefore, because according to our definition, events have a wide scope, we can exploit spatial redundancy to deploy multiple sensor nodes that will allow us to determine when unusual measurements are consistently observed and hence report an event. This is a focused and convenient definition that supports a obvious solution for the distinction between faults and events. In reality, the relevance of physical phenomena for the monitoring process (i.e., if the effects of such phenomena on measurements should be perceived as a fault or as an event) depends on the application. For instance, the application might be interested when a boat crosses a determined limit, hence a collision of the boat with a sensor is considered a relevant event and not an outlier. On the other hand, when a lightning causes an increase of the lighting conditions, if we have several luminosity sensors, all detecting an event, for the purpose of a certain application for smart homes to open curtains according to existing light, it is an important event and not an outlier. The definition of event as we introduced, makes the aquatic monitoring problem more approachable and not so application dependent.

Faults, differently from events, are considered in this thesis as a defect in the sensor, occurring either in the hardware or in the sensing processes. Also, we regard errors as the effect of sensor faults and its manifestation in the deviation from an expected measurement into a faulty measurement, possibly leading to a failure of the monitoring system.

In controlled environments it is easy to deal with localized events and distinguish them from faults. This is because, in these environments, the possible set of localized events may be known a priori. If these events have distinctive signatures observable through sensor measurements, then they can be easily recognized.

However, in a natural environment, as considered in this thesis, the range of events is very wide and heterogenous. It is very hard to define all specific event signatures which could help to detect the events and differentiate them from faults. This is why in these environments we consider localized events as a fault.

Given that we use redundancy and we have to compare several measurements, the next issue to be addressed is what kind of conclusions can be derived from these comparisons. For that, we consider the notion of sensor nodes state.

If the sensor is performing as expected, which can be determined by analyzing the data produced by the sensor using some data processing method, then it is considered to be in a normal state. If the data processing method detects the existence of some anomalous measurements, then it is said to be in a failure state. Finally, it is possible that these anomalous measurements are also observed in the output of all other sensors. In this case, all the sensors are in a event state. Otherwise, we need to reason in terms of the majority of observations. If the majority of nodes produces measurements showing anomalies, then the network is in an event state. Otherwise, the network is in a normal state and the minority of nodes that are not performing as expected are in a failure state.

The above definitions become particularly important when exploring the spatial correlations between neighbor sensors in order to correctly identify both the event and the failure behavior [136].

In summary:

- Unlike events in controlled environments, an aquatic-related event does not have a previously known signature, so the detection of these events requires redundancy.

- Temporal correlations based on time series data of a single sensor node are the first indicator of a potential failure. Therefore, temporal correlations are relevant.

- Spatial correlations with neighbor sensors will determine if an hypothetical change of behavior is part of an event. Considering the typical structure of an aquatic monitoring network, proximity or higher correlation (see Section 3.4) should be considered and:

  - if the majority of neighbors are not experiencing a change of behavior, a failure mode scenario is highly likely;
  - if the majority of neighbors are witnessing a change of behavior, an event is highly likely and a failure situation is unexpected;
  - if the neighborhood is mixed, a query to the most correlated and closer neighbors will increase confidence in the result;

  Therefore when using redundant sensors, it is important to ensure that they are spatially correlated.

- Value redundancy provided by redundant sensors measuring in the same location can also partake on an important view of the event scenario, allowing for a very accurate distinction between failures (affecting only one sensor) and events (affecting both). Therefore this should be the most recommended approach to perform this distinction. However, multiple sensors in one location it is not common in aquatic networks, for cost reasons.

Therefore, to design a generic methodology it is important to exploit redundancy both in the time and value domains. In addition, although without specific implications in the definition of the generic methodology, in the selection of the sensors for value redundancy the need for spatial correlation must be considered as an explicit requirement.

4.2.3 Estimation for detection and correction of failures

In this thesis, in the design of a generic solution for dependable quality monitoring, we need to distinguish the classification and prediction techniques in order to support the choice of appropriate algorithms to identify sensor failures.

In the previous chapter, we focused on prediction techniques for estimation purposes. However, when it comes to defining a generic methodology, classification techniques should not be excluded a priori.

In Chapter 2, we already introduced and provided examples of applications of both types of techniques as part of the taxonomy overviewed in Figure 2.3. Classification is characterized as a system state oriented method, while prediction is considered as system data oriented. This difference can be reflected in terms of outputs, with implications on its applications. While classification provides a discrete response, prediction techniques outputs in a continuous domain.

Typically, we use classification when some decision needs to be taken. For instance in a risk-based system divided by classes, the object of the system can be classified according to available datasets and a learning algorithm. So, a classifier makes a decision within a finite range of classes in which class dataset is likely to be inserted in.

Therefore, if the goal is to detect whether a measurement or a set of measurements are part of a failure behavior, we can use classification algorithms, capable of classifying into normal and abnormal classes (or even directly into the failure modes), since these techniques are appropriate to perform such decisions.

Regarding prediction techniques, additionally to the applications in Chapter 3, these techniques are especially used when there is an assumption that the involved system can be modeled with the provided dataset, through an unknown function. This can be done via a regression algorithm for parameter or with density estimation, for instance. Extracting the unknown function enable us to produce estimations based on the extracted model.

The purpose of the methodology is not only to detect failures in measurements but also to characterize the quality of each measurement and if this quality is below some threshold, be able to provide an estimation of a replacement measurement with better quality. Therefore, a solution for dependable data quality needs to encompass the decision-making capabilities of a classifier in order to detect faulty measurements, as well as the prediction mechanisms to model the sensors behaviors to estimate expected values for the measurements. However, this classification does not necessarily need to be based on machine learning approaches. Therefore, for the purpose of defining a generic methodology, both types of capabilities, that is, detection and estimation, are necessary.

The proposed methodology described in the next section encompasses the use of prediction methods to estimate the expected sensors measurements, which in practice exploit machine learning techniques. The methodology also encompasses failure detection but in this case the concrete techniques to implement failure detection are not based on machine learning. The concrete solutions are described in chapters 5 and 6.

4.3 Methodology overview

In this section a dependable monitoring methodology, explaining in detail when and how it can be applied to assess the quality of collected sensor measurements and improve their quality, is proposed and described. The methodology is defined to be generally applicable to any WSN monitoring system in harsh environments. This is accomplished by defining essential functionalities. The described methods are proposed independently of the physical processes being monitored, but leaving room for the selection of methods whose results depend on the concrete behavior of the monitored processes. A presentation of the considered system model on which the proposed methodology relies is done initially. Then the methodology, explaining step by step how the sensor measurements are handled by a sequential chain of building blocks, is presented.

4.3.1 System model

A WSN architecture composed of $N > 1$ sensor nodes is assumed where each node is equipped with one or more sensors measuring different, but somehow correlated, physical processes (e.g., wind speed and atmospheric pressure, or water temperature and conductivity). Sensor nodes may be physically distant, but the measurements produced by similar sensors (e.g. water level) are also somehow correlated. The WSN has a gateway or sink node that receives all sensor measurements, but no specific assumption is made on the WSN topology as long as data transmitted by each sensor node can reach the sink through the WSN. The sink node is responsible for processing sensor measurements using the proposed methodology, making the dependable monitoring data available to other systems upstream (e.g., for storage or early warning purposes).

Regarding temporal aspects, sensor nodes are assumed to be configured to periodically transmit a new measurement, but no assumption is made on the frequency of transmission nor on the synchronization between different sensor nodes. Message transmission delays are assumed to be negligible in comparison to the dynamics of the monitored physical processes. Furthermore, all measurements received at the sink node are considered to be assigned the timestamp obtained from its local clock, allowing temporal correlations between independent measurements to be considered by the processing methods. The local clock at the sink node is assumed to be correct.

Regarding the assumed fault models, there is a specific focus on sensor data with outliers, drifts and offsets, regardless the nature of these value faults. Also, the handle of omissions (i.e., sporadic loss of a measurement) and crash of sensor nodes are considered, as well as how lost information is recovered. In the case of crash failures, however, this recovery is only partial. Moreover, if f sensor nodes crash, we assume that $N - f \geq 2$. The sink node is assumed to be always correct.

4.3.2 Framework

A methodology for processing measurements from multiple sensors is proposed, which is typically done at the sink node. As an outcome of this processing, the confidence level on the quality of measurements of target sensors is derived and corrected measurements, whenever the received ones are considered faulty, are produced.

While the methodology is intended to be used for the runtime detection of sensor faults and mitigation of measurement errors, it can also be used to process datasets that have been collected previously, with the purpose of data analysis and correction. In fact, the application example and respective results that we present in Section 5.3 are based on already existing datasets.

The methodology requires several models for the correct behavior of each sensor to be created, using one or more supervised learning approaches. Therefore, a preliminary step is to construct these models, which requires correct sensor data from all the sensors to be used. At least three models must be created for each sensor, one exploring temporal correlations between consecutive measurements of the target sensor, another exploring spatial and value correlations between measurements of the target sensor and measurements from a variable number of other sensors, and the third one only exploring the correlations between the target current measurement and the measurements of the other sensors. More models may be necessary to further explore the correlation level among the sensors.

The methodology is designed as an ensemble of supervised learning methods, which require an offline initial training phase for each model construction (prediction techniques). Furthermore, the methodology encompasses 4 additional blocks, all of them with capacity to be performed in runtime and for each new received measurement from each target sensor, which are the following:

- *Prediction (P)* – When a new measurement is received, its quality must be assessed. Given that the ground truth is unknown, one possible approach is to employ prediction methods for obtaining one or more estimates of that ground truth, which will be used in subsequent processing blocks with the final objective of evaluating the quality and possibly determining a replacement value with better quality.

- *Failure Detection (FD)* – The purpose of Failure Detection is to identify possible failure behaviors in the dataset. This block consists of procedures to characterize a measurement as normal or abnormal, in which case a failure situation is considered to exist. This block must also consider that an apparent anomaly on a measurement might be caused by a real environmental event and not a sensor fault, thus not signaling the measurement as faulty.

- *Quality Evaluation (QE)* – Using the outcome of the previous blocks, a quality coefficient for the measurement can be determined. If a measurement is considered faulty, this coefficient is set to 0. Otherwise, it will take a value that may be at most 1.

- *Measurement Reassessment (MR)* – If a measurement is faulty, it should not be used to prevent error propagation with potentially nasty consequences. Instead of simply removing the faulty measurement, this block aims at mitigating the detected fault by determining an estimate of the expected value of the measurement with sufficiently good quality.

4.3.3 Building blocks

A flow diagram of the 4 blocks of the proposed methodology is provided in Figure 4.1. Below we describe each block, considering the necessary inputs (current and past sensor data samples) for the involved techniques and the respective outputs.

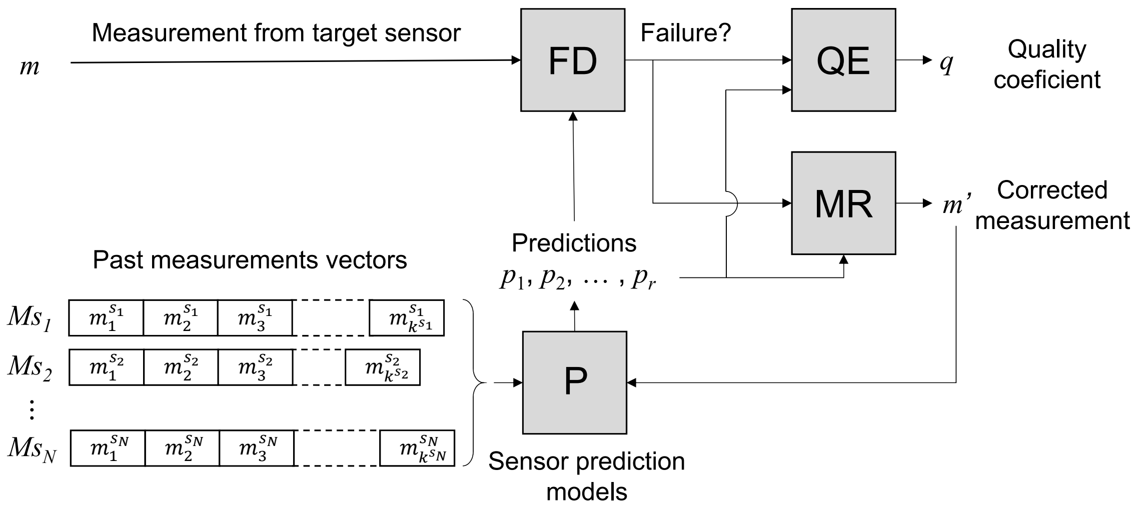

Figure 4.1: Flow diagram of the methodology.

An initial time interval is assumed, during which measurements from all sensors are collected but not processed. This allows to build historical datasets of past measurements for each sensor s_n, represented in Figure 4.1 by vectors Ms_n, which are essential for the Prediction block (P block in Figure 4.1). This block starts whenever a new sensor measurement m is received from one of the sensors, referred to as the target sensor when employing the methodology to process m. For each sensor s_n, with $n \in [1 \dots N]$, the vector Ms_n is defined as follows:

$$Ms_n = [m_1^{s_n}, m_2^{s_n}, \dots, m_{k^{s_n}}^{s_n}] \tag{4.4}$$

Each element of Ms_n is a past measurement received from s_n. The size of Ms_n, k^{s_n}, may vary for each sensor s_n. This size depends on two aspects. Firstly, it depends on the characteristics of the environment variable being monitored by s_n. The rule of thumb is that the vector must include enough measurements to characterize the temporal scales of relevance with enough resolution for the phenomena at stake. For instance, if measuring the outside air temperature, there is a 24 hours cycle that should be completely included in order to represent in this vector the daily variability of this variable. If an annual assessment is the target, then historical data should comprise winter to fall data. Secondly, it depends on the frequency of sensor s_n measurements. If the air temperature sensor provides a measurement every hour, then the size of Ms_n should be at least 24. The frequency should be adequate to properly characterize the phenomena.

In addition to the measurement vectors for each physical sensor, the prediction block may benefit from other information sources, that provide measurements somehow correlated with the target sensor ones. For instance, a meteorological forecast model can be used as prediction of the air temperature at the sensor location, acting as a virtual sensor providing measurements to insert in an additional Ms_v vector.

Also, although the temporal dimension is important when correlating measurements from multiple sensors, since there are no requirements that the measurements in Ms_n vectors are temporally synchronized. Sensors with different monitoring frequencies, producing measurements in different temporal instants, will necessarily generate unsynchronized Ms_n vectors but possibly correlated.

Given the several Ms_n vectors that provide past knowledge concerning the monitored environment, the objective is then to deploy data fusion techniques to obtain a set $P = [p_1, p_2, \ldots, p_r]$ of r predictions p_r for the expected measurement of the target sensor at that point in time.

For data fusion, the multiple sets Ms_n can be considered as features. Therefore, by selecting different features, several predictions can be obtained resulting from the selected combinations, even if using only a single sensor fusion technique. For instance, in a system with air temperature, atmospheric pressure and light intensity sensors, predicting a temperature value at some point in time is possible by using a combination of past measurements from the temperature sensor itself and the light intensity sensor, or from the atmospheric pressure and light intensity sensors, not including the temperature sensor. While in this example the correlation between the different physical variables is not obvious, it is still exploitable, the availability of other air temperature sensors in the neighborhood, providing directly correlated measurements due to spatial proximity, could also be explored.

In fault-free situations, all predictions will be redundant relatively to the input measurement m. However, if some fault occurs, either affecting measurement m or some predictions p_r, then significant differences between some of these values may be observed. These differences are handled in the next blocks of the methodology.

The second block, Failure Detection (FD), is aimed at determining if measurement m received from the target sensor is faulty. This requires a method to assess if m is significantly different from one or more of the elements in P. For the sake of keeping the methodology generic, no specific comparison method is prescribed to compare m with the predictions in P, as the most appropriate method depends on the failure mode and, once again, on the concrete variable (and associated dynamics) being considered. In Chapter 5, a concrete approach for outlier detection based on a statistical method is proposed. The method uses the distribution of square differences between measurements and predictions, but other methods may be used, such as moving averages, comparison with thresholds or machine learning (for instance, the aforementioned classifier methods).

With those appropriate techniques for the predictions and a feasible comparison method defined, the detection of any determined sensor failure is possible. The expected outcome of FD is a Boolean state related with the positive or negative detection of a failure. With this information and with the outputs of the Prediction block, next actions are to determine the confidence in the measurement m, which is done in the Quality Evaluation block. The result of this processing block is a quality coefficient q such that q is in the interval $[0, 1]$, being 0 the lowest and 1 the highest possible quality. This confidence value can be obtained through an evaluation method that, for example, calculates the significance of the differences between m and all predictions in P. If m is similar to all predictions, the outcome will be a high-valued coefficient, meaning that the measurement is trustworthy and may be used in other contexts. If q is below a given threshold, it is important to correct the measurement, which may be once again done using the existing predictions.

The Measure Reassessment block is performed by considering vectors Ms_v and P for the calculation of an appropriate measurement m', removing the identified failure behavior. For instance, one possible solution for an outlier failure is to consider m' as the average of all predictions in P or the predictions over significant time scales (for example, in an aquatic monitoring system, we can use the average values using a tidal cycle as time scale).

All four processing blocks are explained herein focusing on particular case of value faults. As matter of fact, the flow diagram in Figure 4.1 itself only overviews one iteration of the methodology during runtime. For the scenario of systematic failures, another step should be considered within the FD, with a method for pattern recognition, where the detection of an event has a repetitive quality decrease during a continuous period of time for that same sensor.

In the scenario of drifting or offset failures, the temporal restrictions change. Contrary to outliers, the detection of these types of failure implicates that a subset of Ms_n may contain a failure behavior and should be looked into it from a perspective of an ongoing failure event. The outputs of the methodology in these situations must include the likely start and end of the failure for the target sensor. Nevertheless, the outputs of QE and MR to the stakeholder are reliable, since for each m in the subset both q and m' were extracted considering the spatiotemporal correlations with neighbor sensors. In Chapter 6, we propose a concrete solution for systematic failures detection.

4.4 Summary

A novel methodology composed by four building blocks was defined herein. For each block, the generically applicable actions that must be taken for dependable monitoring in any considered environment, independently of the concrete monitored variables, are described. To illustrate its applicability and validity, in the following chapters, the application for outlier detection (Chapter 5) and systematic failures (Chapter 6) in a complex river-estuary aquatic monitoring system is promoted and detailed, providing concrete instantiations of methods to implement the described steps and focusing on the detection of the respective faulty behaviors.

The selection of different data fusion techniques for each of the blocks is dependent on the application and the environment variables being monitored, which may cause some approaches to be more suitable to one particular case study. Therefore, the methodology was kept in its essence generic by not enforcing a specific technique to be used.

To solve the instantiated problem of systematic faulty behaviors, contrary to the more common outliers scenarios, the methodology comprehends, in the FD block, an event detector for continuous quality decrease, while maintaining the validity of the outputs of the other blocks for past measurements.

To address the distinction between failures and events, both P and FD blocks are designed to compare the different spatial and temporal correlations, in order to correctly identify the failure situation, even during a natural event.

Finally, the MR block outputs a corrected measurement for the situations when quality is below the expected. This corrected measurement is extracted via the predictions generated initially in P block using sensor modeling methods and estimators.

Chapter 5

Dependable outlier detection

5.1 Introduction

The proposed methodology, presented in the previous chapter, makes use of spatiotemporal similarities between neighboring nodes in a sensor network, which enables a correlation between the sensor nodes measurements. This is supported on the fact that sensors readings in an environment usually tend to have a higher correlation for sensors that are geographically closer to each other (spatial similarity), and also higher correlation for a recent period of time (temporal similarity) [115]. Considering this assumption, faulty data observations should be uncorrelated, while environment-related observations are likely correlated (see also in Section 4.2.2).

In this chapter, we consider that faulty data observations are due to spurious errors, such as outliers, and we instantiate the methodology proposed in the previous chapter to deal with these errors. This instantiation is focused only on outlier failure detection and exploits predictions performed using machine learning techniques.

This instantiation is evaluated using concrete datasets from sensors measuring temperature and salinity parameters in water. The objectives are to show that outliers can be effectively detected, that the quality of measurements can be adequately quantified and that low quality measurements can be replaced by accurate measurement predictions. Also, by successfully defining an instantiation of the methodology we implicitly validate it.

To show that the defined failure detection and machine learning techniques used in the instantiated monitoring system are effective and advance the state-of-the-art, we consider a public dataset (IntelLab, presented in Section 2.5.1) and we compare the results obtained with our monitoring system with results provided by three state-of-the-art approaches using the same dataset.

In Section 5.2 related work on mechanisms for detecting sensor faults is reviewed, including the use of machine learning strategies. A concrete instantiation of the methodology presented in the previous chapter is then provided in Section 5.3. The application for outlier detection in real sensor data collected from a river-estuary aquatic system is considered, describing the concrete solutions that were devised for each of the methodology steps and showing their effectiveness. To further validate these solutions, the results of a comparative analysis against three state-of-the-art approaches is provided in Section 5.4. The comparison shows improvements by using the proposed solution in the detection of such failures. Finally, Section 5.5 summarizes the chapter.

5.2 Related work

An outlier, as defined in [47; 193], "is a subset of observations which appear to be inconsistent with another dataset". It can also be defined as "measurements that are deviated from the expected dataset". Faulty data, such as outliers, is normally represented as an arbitrary change significantly different from the remaining data, and it should be corrected when possible.

Dependable monitoring in environment systems rely on a correct characterization of the involved phenomena, of the possible issues affecting sensor data, related faults and respective fault models. In the past decade there have been many studies supporting the use of machine learning techniques and sensor fusion to identify or classify events, including failure situations. Herein, we focus on the most relevant ones for our target: dependable monitoring in complex environments such as aquatic systems.

Many researches consider outliers and events in a similar category, dealing with both similarly. In [32] the authors presented a sensor-fusion solution to detect events in a WSN via a classifier technique and a decision-maker on a supplementary layer (WSN sink node). This classifier can either be based on an artificial neural network (ANN) or on a Naïve Bayes algorithm, where both techniques present low computational complexity allowing real-time detection of the event. The solution is then applied to a fire alarm network dataset, with some additional noise and sensor loss, to prove its accuracy.

Still regarding event detection using machine learning, a sensor fusion solution is portrayed in [33] where, for each node, there is a decision tree trained to verify if that node detects an event. On a sink node there is a voter algorithm (requiring additional training) that gathers every node decision and concludes on the final result. This solution was also tested with a fire alarm network dataset, both for accuracy and computation complexity.

Given that an event can also be characterized by an abnormal reading or set of readings, most of the advances in this area are related to fault detection. In [124] a neural network was trained to perform sensor data fusion and detect abnormal behaviors in the sensor network, more specifically in outlier detection in WSNs.

Regarding specifically outlier detection, several surveys on the subject have been published, characterizing and grouping many of the works on this subject [30; 82; 83; 151; 159; 193; 199]. Some of the authors focus on more specific aspects, but they all separate outlier detection approaches into the following categories: *statistical-based*, using probability models to capture the distribution of data and to assess if a measurement is an outlier; *nearest neighbor-based*, calculating a similarity to measure between two data measurements; *clustering-based*, used as a data mining approach to group similar sensor measurements into clusters with similar behavior, whereas outliers do not belong to any cluster; *classification-based*, training a classification model using a set of sensor measurements and classifying an unseen measurement into the learned class; and *spectral decomposition-based* which aim to use principal components analysis (PCA) to find normal behaviors in sensors data. Some of the authors prefer to categorize the fuzzy-logic and artificial neural networks (ANNs) as *artificial intelligence-based* approaches, but their purpose is similar to classification-based.

Many examples of solutions for each category can be found on the mentioned surveys but a brief overview with recent works is provided. A solution based on a k-means clustering approach is provided in [25], where the authors present a clustering methodology together with a statistical approach to verify the existence of outliers in a temperature sensor network deployed in buildings. This example is particularly interesting for the present work since it is also environment monitoring-related as temperature sensors are affected by the sun. On the classification-based category, a recent research [129] has shown that an adaptive Bayesian network can be used in the sensor nodes to cooperate in classifying the measurements. The novelty of this work is a distributed algorithm that builds the network with increasing complexity according the number of the outliers in the dataset. A solution based on fuzzy-logic and similarity measures (nearest-neighbor-based approach) is depicted in [95], through an algorithm that calculates the temporal and spatial similarities between measurements, assuming that these are highly correlated. Providing the similarities to a fuzzy-logic system, the output will be compared to a prefixed threshold to determine if there is an outlier. In [76] an algorithm based on PCA is proposed, using Mahalanobis distance induced feature subspace by principal components to verify if the distance of a new measurement is above a prefixed threshold.

In all the above examples there are two common concerns, the importance of the accuracy rate in each technique and the respective complexity, as most of the solutions are intended to be partially deployed in the sensor nodes, for real-time outlier detection. In [29] a performance comparison study of the major outlier detection techniques is presented. This study presents an overall evaluation based on strengths and weaknesses, the respective computational complexity analysis, and a simple experimental study measuring the detection rate and false positive rate, concluding that support vector machines (SVM) techniques outperform techniques based on Bayesian and neural networks, decision trees, and nearest neighbors. Interestingly, in [142] a technique based on PCA is compared with two solutions based on SVM techniques, showing that the latter ones underperform in outlier detection. The results obtained using our techniques contradict these observations. In fact, as we show in Section 5.4, the accuracy and completeness of our outlier detection solution favourably compares to results presented in [142], where both SVM and PCA approaches are used.

Another characteristic of previous studies is that most of them do not consider datasets obtained in harsh environments. As mentioned in [154], these environments are "high stress environments which offer severe monitoring and communication challenges". They also refer that, in such environments, both outlier and event detection are particularly important and consider four steps to perform it correctly: *outlier labelling* or detection; *outlier cause* for the determination of its source; *event identification* or detection; and *outlier accommodation*, when the outlier is regarded as part of the sensor data for future applications. However, this thesis does not provide a dependability oriented methodology that incorporates these steps to address the challenges of harsh environments, nor are we aware of any work that does so. Our work provides contributions in this direction.

5.3 Instantiation of the methodology

To demonstrate how the proposed generic methodology can be instantiated, we consider here its application to outlier detection in datasets collected from a real environmental monitoring system. Therefore, in Section 5.3.1, we describe briefly the considered river-estuary aquatic system and its dynamics. After that, Section 5.3.2 describes the complete ANNODE (Artificial Neural Networks Outlier Detection) solution. It details how the generic methodology can be applied in the considered aquatic system, focusing primarily on a technique for predicting sensor measurements which is based on machine learning and, more specifically, on ANNs. To complement the prediction technique, we also address specific strategies for failure detection, quality estimation and measurement reassessment. In this section we also discuss the appropriateness of the ANNODE solution to the specific characteristics of the aquatic environments.

In Section 5.3.3 the results obtained through the instantiation of the methodology and techniques to detect outliers in the case study dataset are presented and discussed.

5.3.1 Case study description

The instantiation of the methodology for outlier detection is evaluated using an operational online environmental monitoring network dataset, mentioned herein as the SATURN case study, already introduced in Chapter 2.

For the purpose of evaluating our methodology, stations Jetty A, Lower Sand Island light, Desdemona Sands light and Tansy Point (Figure 2.5, highlighted from left to right respectively) were selected, as correlated data is available for temperature and salinity variables, during common periods of time and at approximate depths. As shown in Section 3.4, the use of sensors providing correlated data is fundamental to exploit redundancy.

Furthermore, for the construction of the several prediction models for the correct behavior of each sensor, as described in Section 4.3.3, we also need to characterize the monitored variables behaviors as completely as possible. This characterization impacts the vectors Ms_n defined by Equation 4.4, which are detailed in the next section.

For the case study, the monitored variables are greatly affected by the tides, having a variability in time according to the tidal influence (harmonic movements) as explained in Section 2.5.2.

Moreover, when using a supervised data fusion technique such as ANNs, it is important to gather a set of information capable of representing completely all the typical variable behaviors patterns.

Therefore, for the instantiation detailed in the following sections, we selected a training dataset for the prediction models that included almost one calendar year from 2009-07-01 until 2010-06-06, with some gaps that were removed from training due to absence of data within. This dataset is represented in Figure 5.1 for all four selected stations with temperature and salinity sensors.

For the application part of this instantiation, where we test and evaluate all the selected methods for each of the methodology building blocks (as defined in the previous chapter, Section 4.3.3), we chose a different dataset. The testing dataset comprising sensors data from 2013-10-01 until 2014-01-01 is represented in Figure 5.2. The goal is to test our solution in a time period different from the training period, which in this case is around three years later.

5.3.2 Outlier detection solution

In the ANNODE instantiation of the methodology, we begin by selecting the sensor nodes that possibly provide correlated measurements, according to their physical location and the involved water dynamics. This selection was presented in Figure 2.6.

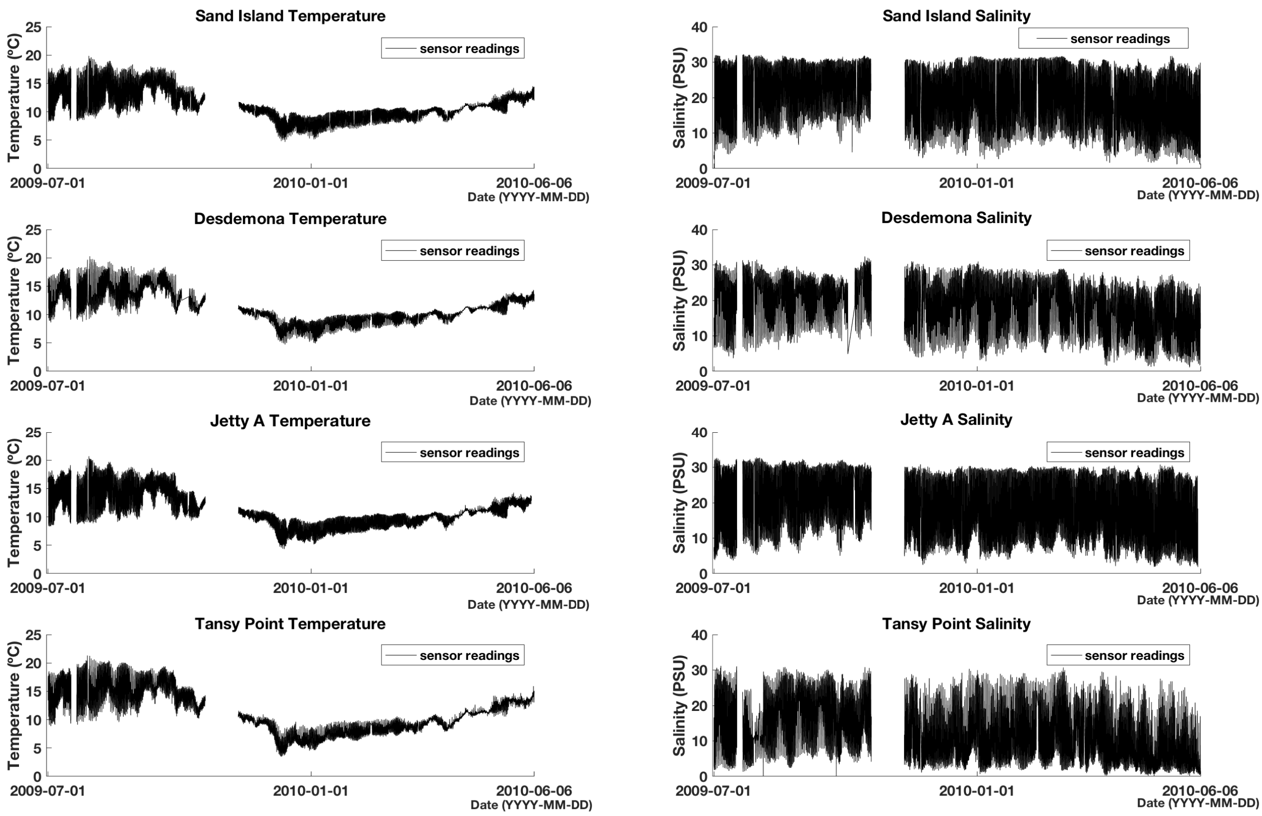

Figure 5.1: Prediction models training dataset

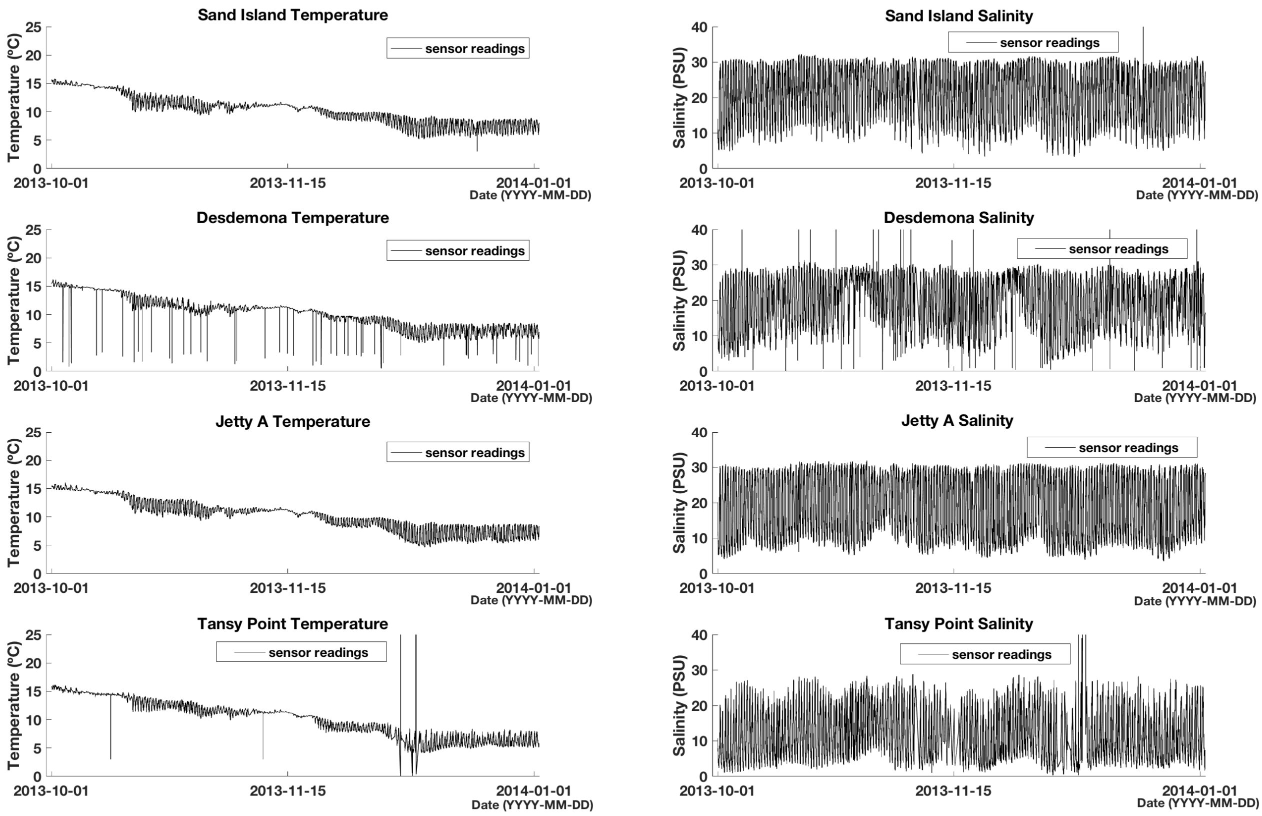

Figure 5.2: Outlier testing dataset

The next step is the selection of a data fusion technique for the Prediction block and the respective training and testing datasets. We have chosen ANNs as the data fusion technique, considering its ability to handle non linear problems and its proven good performance in modeling sensor behaviors by estimating its measurements, as concluded in Section 3.3.3. Regarding the datasets, we detailed already in the previous section the different training and testing periods. Also, as expected from datasets in harsh environments, they have gaps, faulty measurements, the sensor measurements are not synchronized and are collected with different frequencies.

In the following paragraphs we will describe in detail how we trained the ANNs to model the selected sensors, thus implementing the Prediction block, also describing the strategies for outlier detection, quality evaluation and measurement reassessment, thus implementing the respective blocks.

Prediction block

Regarding the configuration of the selected ANNs, we adopted a feedforward ANN and implemented it using MATLAB *fitnet* function (Deep Learning toolbox), in particular a multilayer perceptron (MLP) consisting of two hidden layers, as shown in Figure 5.3, with each neuron capacitated with a hyperbolic tangent sigmoid (*tansig*) as the activation function. The MLP uses the training dataset to model the target senso via the Levenberg-Marquardt algorithm [46].

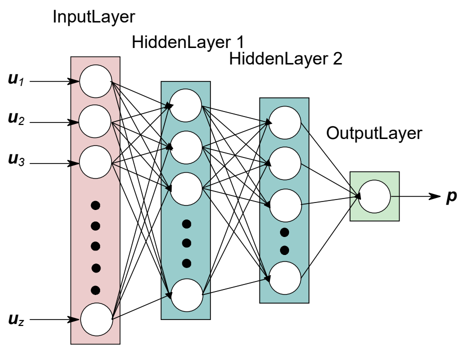

Figure 5.3: ANN MLP structure.

This structure was used to build all the prediction models, using different configurations of inputs by combining datasets from different sensors. Moreover, as emphasized in the previous section, the training datasets represent one calendar year for a complete characterization of the sensor behavior. Finally, these training datasets were constructed using data considered to be free from faults.

In addition to the training datasets and the ANNs configuration, it is important to define the desired ANNs inputs and outputs. This definition is denominated features selection. We already identified the output as an estimation of the target sensor next measurement, a single value prediction. In the inputs, we want to describe each sensor view of the system by providing the ANNs with the best information available in order to learn all possible correlations (value, temporal and spatial).

Therefore, the ANNs inputs can be comprised with information from other sensors of the same stations (or in the same physical space). In this case we considered salinity measurements as an additional input to the ANNs (salinity dataset are shown in Figure 5.1). Our goal is to use this information to exploit the possible correlations that may exist between different types of sensors, in order to correctly capture the environment-related events and to distinguish them from sensor failure situations.

Considering the number of possible input datasets (four temperature and four salinity), we can train several ANNs to model each sensor. In this instantiation we construct the Prediction block by using and training three ANNs for predicting the output of each sensor. Furthermore, as discussed in Section 4.3.3, one of the ANNs uses as input only the past measurements of the target sensor. The other two ANNs use, respectively, the past measurements of the three neighbor sensors and all past measurements from the target sensor and its neighbors.

Consequently, and instantiating the methodology introduced in Chapter 4, the inputs of the ANN that predicts p, ANN_p, consist in a set of Ms_n vectors as expressed in Equation 4.4, with measurements from each sensor s_n considered for that prediction.

$$U = [Ms_1 Ms_2 \ldots Ms_n] \tag{5.1}$$

For instance, an ANN trained with only the last measurements of the target sensor s_v would have as input U (Equation 5.1) the vector Ms_v.

For this instantiation and case study, there are two other aspects related with the ANNs inputs that require optimization. First, as mentioned in the previous section, in the definition of the Prediction block (Equation 4.4), the size of the vector of the last measurements, k^{s_n} corresponding to the number of neurons of the input layer of the ANN, must be sufficiently big to fully characterize the M_2 tidal constituent. Therefore, the vector must contain enough measurements to cover the 12 hours and 25.2 minutes. Secondly, choosing k^{s_n} depends on the monitoring frequency (most of the sensors in the case study produce a measurement every 6 minutes) and on the training and learning process. In concrete, we used 60 neurons in the input layers as this is a good trade-off between all the mentioned concerns (representativity, avoidance of over-sampling and noise). This means that for the ANN trained only the last measurements of the target sensor, k^{s_n} took the value of 60, whereas for the other ANNs this value was 20 for each of the three neighbor sensor input vectors.

Concerning the structure of the ANN in terms of number of hidden layers and number of neurons on each layer, we used the configuration that was found as the best one as explained in Section 3.3.3. In concrete, based on the information provided in Figure 3.13, an ANN structure with 20 neurons on the first hidden layer and 15 neurons on the second was the one showing the best results and hence was selected for this instantiation. We constructed all prediction models for each of the selected sensors using the above defined ANNs, which implement the Prediction block, considering the three types of the ANNs inputs, that is, based only on the target sensor past measurements, based on the measurements of the target and neighbor sensors and using only the neighbors measurements. Therefore, in total we trained twelve ANNs.

Failure Detection block

Regarding the Failure Detection (FD) block, we need to select a comparison method (which can also be a classifier) for the failure detection, as mentioned in Section 4.3.3. The goal of this method is to check if the measurements differ from the predictions, that is, the ANNs outputs. For this purpose we adopted a statistical technique similar to the one described already in Section 3.3.2. This method is used here given its ability to learn the statistical distributions of the differences between the measurement m and each of the three ANN predictions, for each selected sensor. We preferred this statistical technique instead of others, such as fuzzy logic, since we already have a considerable amount of data available in the case study dataset and, based on the supervised aspect of the ANNs, we are able to calculate the probability distribution fitting for the square errors between measurements and predictions.

This statistical technique can be briefly explained as follows. We consider m being the target sensor measurement, and p_i where $i = 1,...,n$ are the ANNs predictions for that target sensor measurement. The goal is to compute the differences between measurement m and each of the n predictions p_i. The purpose is to characterize the distribution of these differences along a training period to further use their probability distribution. For that, we require again a training dataset, in which we collect the differences between the actual measurements of the target sensor and each respective prediction p_i.

Provided the collected differences derived from the measurements extracted from a training dataset and the ANNs predictions based on that particular training dataset (we note that for this instantiation the ANNs were already built according to the aforementioned structure and configurations), we can extract the probability distribution from each set of differences. For instance, if n equals to three, then we have three different prediction models for the target sensor measurements thus we need to learn three probability distributions, one for each of those prediction models. If the distributions are known or to be well described by a particular known function, then the learning consists in fitting that function to the distribution by estimating the distribution parameters. For example, a normal distribution is defined by its mean and variance.

For the methodology instantiation here, we calculated the fitting of the differences based on the square errors (e) for the target sensor measurement m and each prediction p_i in the Prediction block, being the square errors calculated by:

$$e = (p_i - m)^2 \tag{5.2}$$

Furthermore, we used a different training dataset from the previously used in the ANNs training, of a period of two months with sensor data not considered before. This dataset for the comparison method training comprised the sensors readings from 2010-08-20 until 2010-10-10 and is presented in Figure 5.4, for all four selected stations with temperature and salinity sensors. Give that this is a training dataset, we made sure that all measurements were correct.

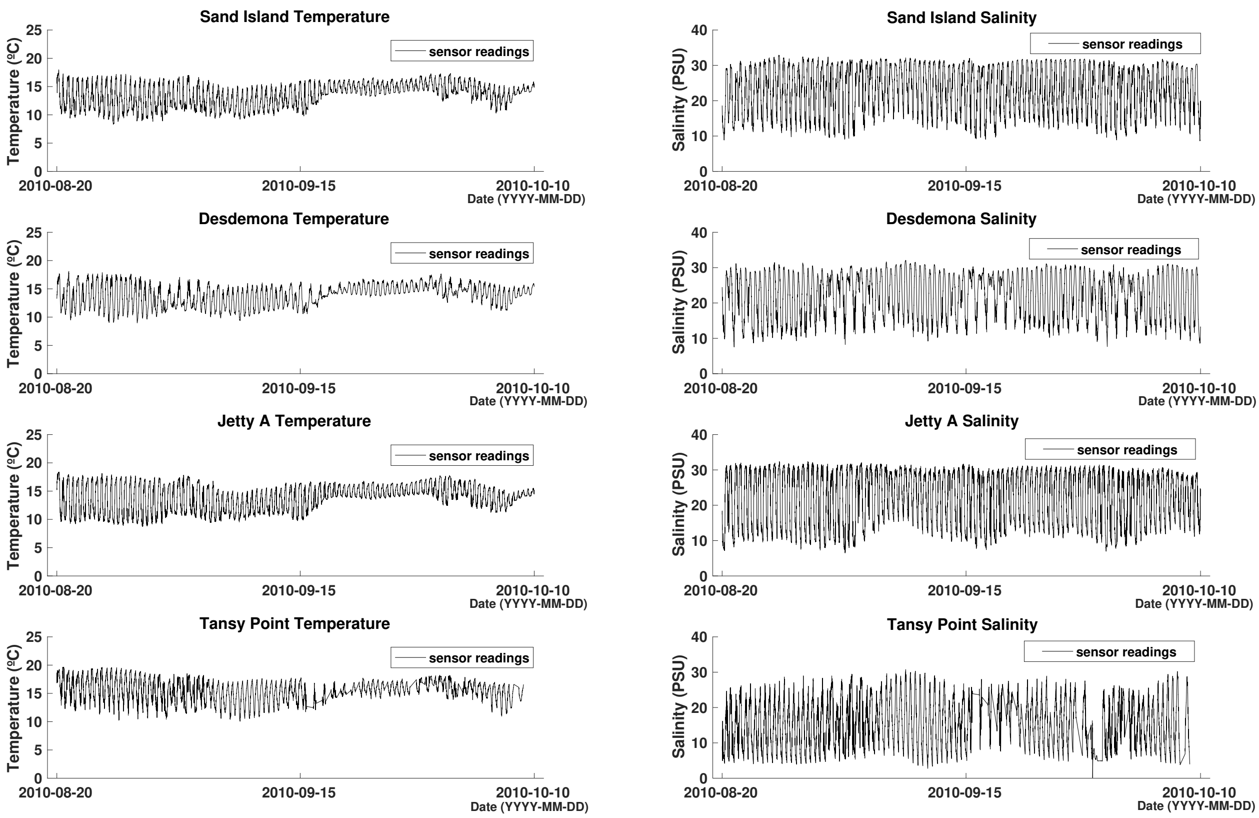

Figure 5.4: Comparison method training dataset

With the ANNs predictions for the above dataset, we extracted the sets of differences for each sensor and respective prediction, based on the expression in Equation (5.2) for the aforementioned period of two months. Based on the observation of the differences, we used a log-logistic distribution function for the fitting as shown in one example of the resulting distribution probabilities, presented in Figure 5.5.

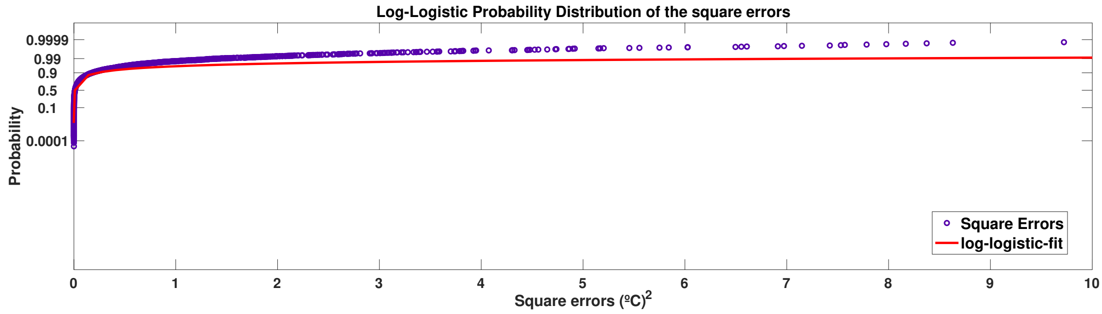

Figure 5.5: Log-logistic probability fit for the square errors.

The log-logistic distribution function was used for its high similarity with the square errors distribution. The fitting was performed in MATLAB using *fitdist* function. Considering the fitting to the log-logistic function of each square errors distribution for all the selected sensors and respective predictions, we can calculate the respective cumulative density function (CDF). For the example in Figure 5.5, the representation of the calculated CDF is provided by Figure 5.6. The purpose of this step is to enable us to calculate probabilities of a hypothetical situation considering the square error e, such as the probability of e being higher than a given threshold. With each CDF we have an automatic method to compare the predictions and the measurement m.

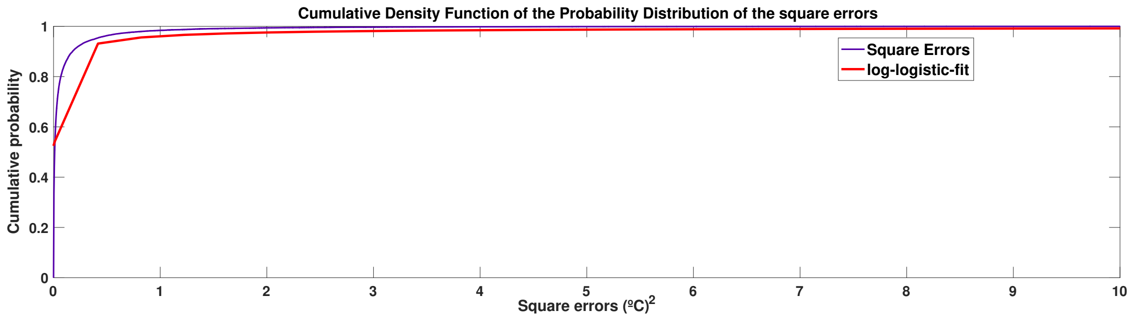

Figure 5.6: Cumulative Density Function of the distribution probability of the square errors.

Moreover, with the provision of the probability from the CDF of a certain error e, we can know what is the likelihood of the difference between the measurement m and p_i being e. This enables us to select a priori a high threshold of this likelihood in order to stipulate how significant, in the context of the known distribution, is that square error e. For example, in Figure 5.7 we defined a probability threshold of 0.8 (80%), displayed in green in that figure, for the CDF already presented (Figure 5.6). With this threshold, we are stating that the differences (errors) larger than the red line are significant. The selection of this comparison threshold and respective impact on the outlier detection results are presented in the next section.

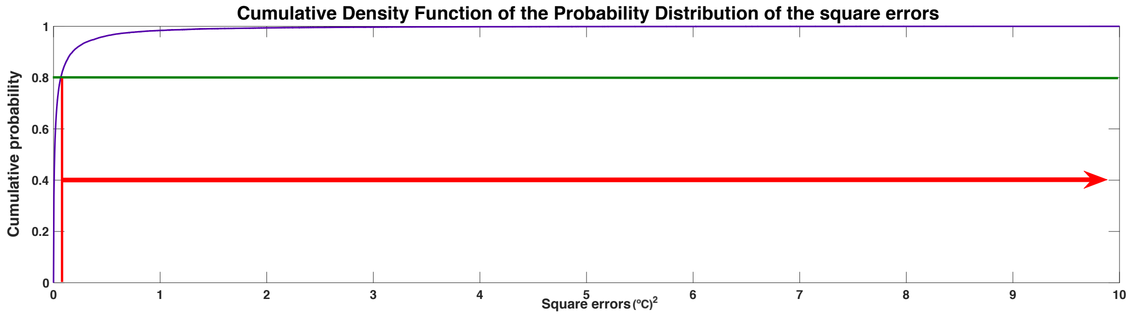

Figure 5.7: Example with the probability threshold of 0.8.

In the Failure Detection block, having the CDFs that model the expected error between the measurements provided by a sensor and a prediction model, it is possible in runtime to verify if the actual measurements significantly differ from the respective predictions. Still, it is necessary to define the strategy to do that. In other words we must define a strategy to assess if a target sensor measurement m is significantly different from the corresponding predictions. The objective is to identify a possible failure affecting measurement m. We perform this detection through the evaluation of a set of conditions, involving the measurement m and the predictions p_i considered in the Prediction block (P).

We define the function $similar(m, p_i, CDF_{p_i}, threshold)$, which implements the comparison procedure explained before. For simplicity of presentation, we consider that the threshold is a constant known to the function and does not need to be always specified and the function knows which CDF_{p_i} to use given a certain p_i. The first condition allows us to distinguish a normal measurement from a possibly faulty one:

$$(\forall p_i \in P) \mid similar(m, p_i) \implies m \text{ is correct} \tag{5.3}$$

If the measurement m is similar to all the predictions, which should be the typical situation, then the measurement is considered to be correct. However, if this condition is false, then this means that there is at least one prediction which is significantly different from m. Different situations lead to this outcome and we go through them in the following.

We start by considering the case where a single prediction is different from m. This can be the prediction that was produced based on past measurements of only the target sensor, the prediction that uses measurements from target and neighbor sensors, or, finally, the prediction based only on measurements from neighbor sensors. In the first case, it is possible to conclude with a high probability that the target sensor is being affected by an event. This is supported by the fact that this event was reflected in the measurements of the other sensors and consequently on the predictions that use these measurements, both of which similar to m. In the last case, it is probable that one of the neighbor sensors is faulty. We exclude the possibility that the target sensor is faulty because in this case the measurement m would be different not only from the prediction using the neighbor sensors but also from the prediction using all the sensors and from the prediction using only the target past measurements. The remaining case, when only the prediction based in all sensors measurements is significantly different from m, is unlikely to occur. In fact, if m is similar to the other two predictions, there is no reason for m not being also similar to the prediction involving all sensors.

If m is significantly different from two predictions (and hence similar to a singular prediction), then only two cases are relevant and one is unlikely to occur. If m is similar to the prediction based on the target measurements, then the measurement is likely correct and the difference with the other predictions can be explained by an event affecting the neighbor sensors or a severe fault affecting only one of them. If m is similar to the prediction based only on the neighbors measurements, then it is possible to conclude that an event is forcing all measurements to take unexpected values. The prediction based only on neighbor sensors uses as input these unexpected values, which justifies that it is similar to m. On the other hand, the other predictions include the target past measurements that force the model to produce a value that is closer to the one that would be expected without an event. The case in which m is similar only to the prediction using all sensors is unlikely to occur because it does not make sense that a prediction using only neighbor sensors and the prediction using only the target sensor are similar to m but that one is not.

Finally, the situation that is indicative of a faulty measurement m is the last possible one, when all predictions are different from m. Therefore it makes sense to define and implement the detection criteria specified by Equation 5.4.

$$(\forall p_i \in P) \mid \neg similar(m, p_i) \implies m \text{ is faulty} \tag{5.4}$$

The strategy to implement the Failure Detection block is appropriate for faults affecting single measurements (outliers). However, for the other systematic failure behaviors, other strategies must be considered. Chapter 6 is devoted to faults of this class.

We test this strategy for outlier failure detection in the next section, using the testing dataset presented in Figure 5.2.

Quality Evaluation block

Regarding the remaining blocks of the methodology, in the Quality Evaluation (QE) block (Section 4.3.3), the goal is to calculate the quality coefficient q that quantifies the confidence in the measurement m. This confidence value can be obtained by calculating the inverse of the average of the cumulative probabilities of each error, for m against all the predictions in P, as shown in Equation 5.5. We instantiate this strategy herein with the cumulative probability functions already established in the comparison method. Therefore, whenever m is not an outlier, q equals that inverse of the average. Otherwise, q is set to 0.

$$q = \frac{\sum_{i=1}^{n}(1 - CDF_{p_i}(e(m, p_i)))}{n} \tag{5.5}$$

Measurement Reassessment block

In the Measurement Reassessment (ME) block (Section 4.3.3), a simple strategy that exploits all the available predictions is proposed. As mentioned, ME procedures promote the replacement of the detected outlier with a new measurement, which is herein an average of all the predictions provided by the Prediction block at that time:

$$m' = \frac{\sum_{i=1}^{n} p_i}{n} \tag{5.6}$$

The next section applies the instantiation in this section to a set of testing datasets. The achieved results allow to evaluate the strategies that were defined for each of the methodology building blocks (P, FD, QE and ME).

5.3.3 Application results

In the testing experiments performed herein, we considered all the above strategies and decisions taken towards the instantiation of the methodology for the detection of outliers in the case study environment and implemented them in MATLAB. The results were obtained considering the goal of identifying outliers and distinguishing them from the environment-related events using the strategies previously described.

In most of the works presented in Section 5.2, the outlier detection algorithms accuracy is measured with a detection rate (DR) and false positive rate (FPR). In this section, given that we use a real dataset from an environment monitoring network with a low number of faulty measurements, the actual number of detected outliers for all sensors in each experiment is also provided for a ground truth baseline. Conclusions are drawn comparing this number with the number of detected outliers in the dataset.

We performed these experiments on the testing dataset with measurements obtained 3 years after the training dataset. It contains around 30.000 measurements of each of the four selected temperature sensors (modeled in these results) during the continuous period of 3 months. In Figure 5.2 the target datasets are presented, in which the following failures were identified by experts:

- *Jetty A* - no failure behavior;
- *Lower Sandi Island Light* - 1 outlier with gaps (no measurements) before and after it;
- *Desdemona* - 44 outliers;
- *Tansy Point* - 11 outliers (a measurement that reached 8000°C was recorded) with gaps surrounding some of the outliers.

For each of these four temperature sensors, we trained three ANNs using the past measurements of the sensors with the training dataset (Figure 5.1), according to what was described in the previous section.

In the previous section, we denoted the existence of a prefixed threshold in the comparison method that must be defined to assert the significance of the differences between the measurement m and its predictions, and thus verify the conditions in equations (5.3) and (5.4). Considering that the selected comparison technique makes use of the CDF function (Figure 5.5) to calculate a probability, the threshold is related to a higher limit of a probability of m being an abnormal measurement (as explained in the example in Figure 5.7). Therefore, several thresholds were tested and verified against the accuracy of the strategy in the FD block for the outlier detection: 0.997, 0.998, 0.9985 and 0.999. The results for each threshold are presented in Table 5.1, with the number of detected outliers for each sensor and the respective detection rate and false positive rate. Given the large number of sensor readings in the testing dataset (around 30000), the low false positive rate is expected considering the small number of true outliers (ground truth). Likewise, whenever any outlier is not detected, the respective detection rate decreases abruptly.

Based on the previous considerations, when observing Table 5.1 results we can assert the importance of selecting the threshold of the comparison technique, visible in the changes of the number of outlier detections in all sensors. When the threshold is set to 0.997, there is a larger number of detected outliers than when the threshold is 0.999.

	Jetty A			Lower Sd			Desdemona			Tansy		
Real Outliers	**0**			**1**			**44**			**11**		
	Detected	*DR*	*FPR*	*Detected*	*DR*	*FPR*	*Detected*	*DR*	*FPR*	*Detected*	*DR*	*FPR*
0.997	*2*	100%	0.009%	7	100%	0.028%	67	100%	0.306%	24	100%	0.121%
0.998	*2*	100%	0.009%	7	100%	0.028%	52	100%	0.237%	15	100%	0.121%
0.9985	*1*	100%	0.004%	4	100%	0.014%	39	88.64%	0%	9	81.82%	0%
0.999	*1*	100%	0.004%	2	100%	0.004%	26	59.09%	0%	9	81.82%	0%

Table 5.1: Experimental results for all sensors and thresholds.

Analogously, we also detect the same variation in the false positive rate, which is necessary low as mentioned. This is expected because when increase the threshold we are being less strict in the similarity comparison, so it is likely than many measurements are not detected as outliers. Regarding the detection rate, two situations are observable. First, for the majority of scenarios (thresholds and sensors) the detection rate is 100%, due to the detection of all real outliers in the dataset. The other situation concerns the Desdemona and Tansy sensor, in particular for the thresholds of 0.9985 and 0.999 where we observe a lower detection rate. Comparing both situations, we verify that the higher detection rate is also followed by a higher false positive rate. This threshold sensitivity analysis is important and impacts the threshold selection for the remaining application.

Among the candidate thresholds, there are two likely choices based on the ratio between detection rate and false positive rate. The 0.998 candidate provides a perfect detection rate for all sensors in the dataset, whereas the 0.9985 threshold produces a lower false positive rate with a relatively low impact on the detection rate, exception for the Desdemona and Tansy sensors. We selected the 0.9985 threshold for the remaining ANNODE solution results herein, as this the one that ensures an insignificant false positive rate. This is mostly important for instance in early warning systems applications. In other applications, for instance for simply sanitizing measurements without immediately using them, it might be more adequate to select a lower threshold, which ensures a higher detection rate. Given the focus on sanitizing, the presence of false positives will be mitigated by the automatic correction in our solution.

We can observe in Figure 5.8 a representation of the outlier detection results for the Desdemona and Tansy Point temperature sensors.The detected outliers are highlighted with red dots. In this figure it is possible to observe the outliers produced by the Desdemona sensor that were not detected, particularly in the final 10 days of the testing dataset. The same situation happens for the Tansy sensor, although it is not as clear in the figure.

We note that in both cases, in each respective dataset, we observe periods during which there is a lack of measurements as well as some measurements with outliers, as described in the beginning of this section. The effect of outliers, if not removed or corrected, is that they introduce errors in the prediction models. The goal of the Measurement

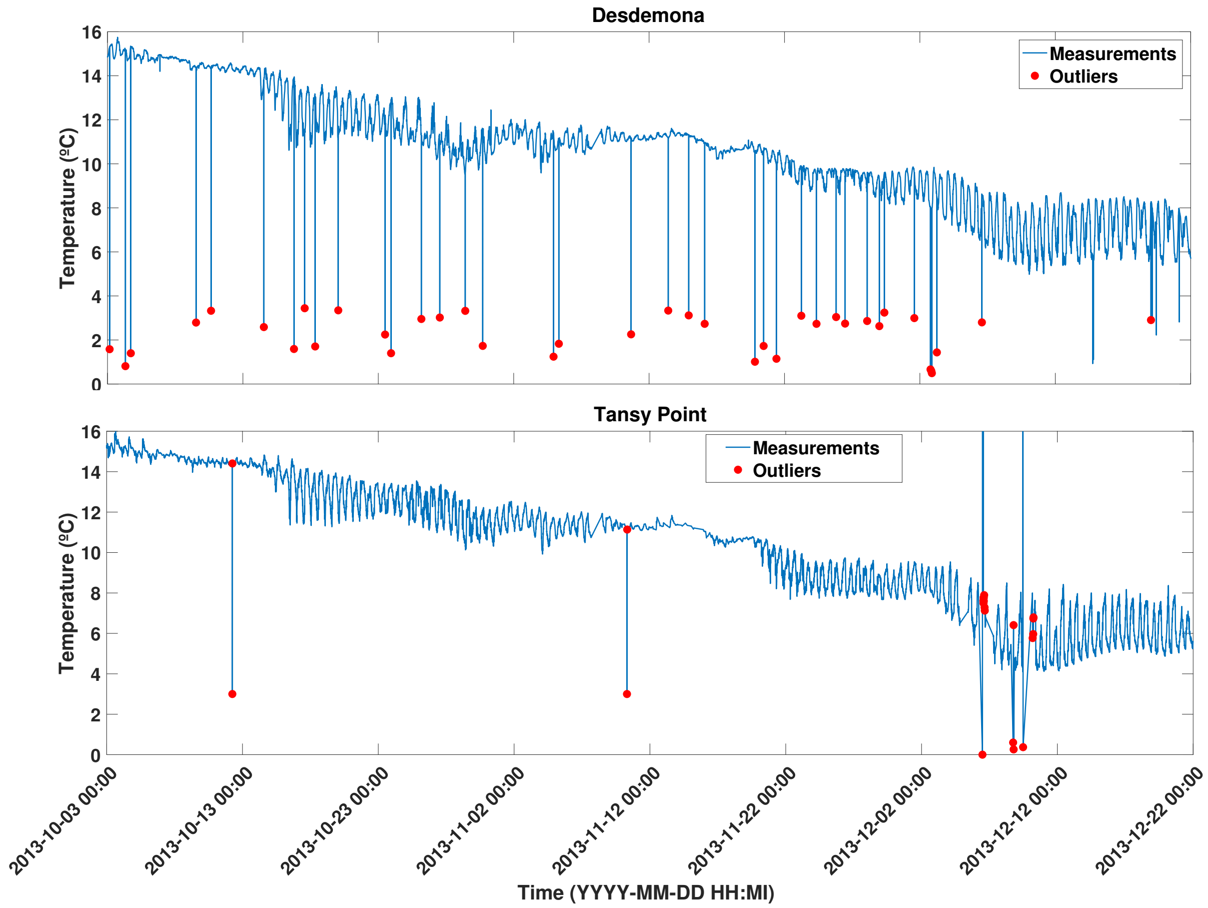

Figure 5.8: Detected outliers.

Reassessment block is precisely to do this correction by replacing the outlier with an estimate of a proper sensor measurement. Concerning the lack of measurements, the implication is that the prediction models, which must be fed with enough measurements to fill a M_{s_n} vector (see Expression 5.1), will end up including older measurements (as newer ones were not received). This means that results of the prediction models in which this vector is used may not be as accurate as they should be. These anomalies, added to the fact that the measurements are affected by noise, make outlier detection even more challenging but, as observed, the employed methodologies were able to quite successfully pinpoint most of the outliers.

In summary, the achieved results demonstrate nevertheless that the selected strategies are quite effective to the detection of outliers in a real highly-variable aquatic system, producing a very low number of false positives even in the presence of the described anomalous situations.

Regarding the strategy adopted in the Quality Evaluation (QE) block, the results are displayed in Figure 5.9. We can observe the output of the QE strategy for both target sensors. We note that whenever an outlier is detected, q is set to zero. Otherwise, q is set using Equation 5.5. In Figure 5.9, we can observe that there are some values of q almost as low as zero that represent the situations in which at least some predictions in P are quite different from the observed measurement m.

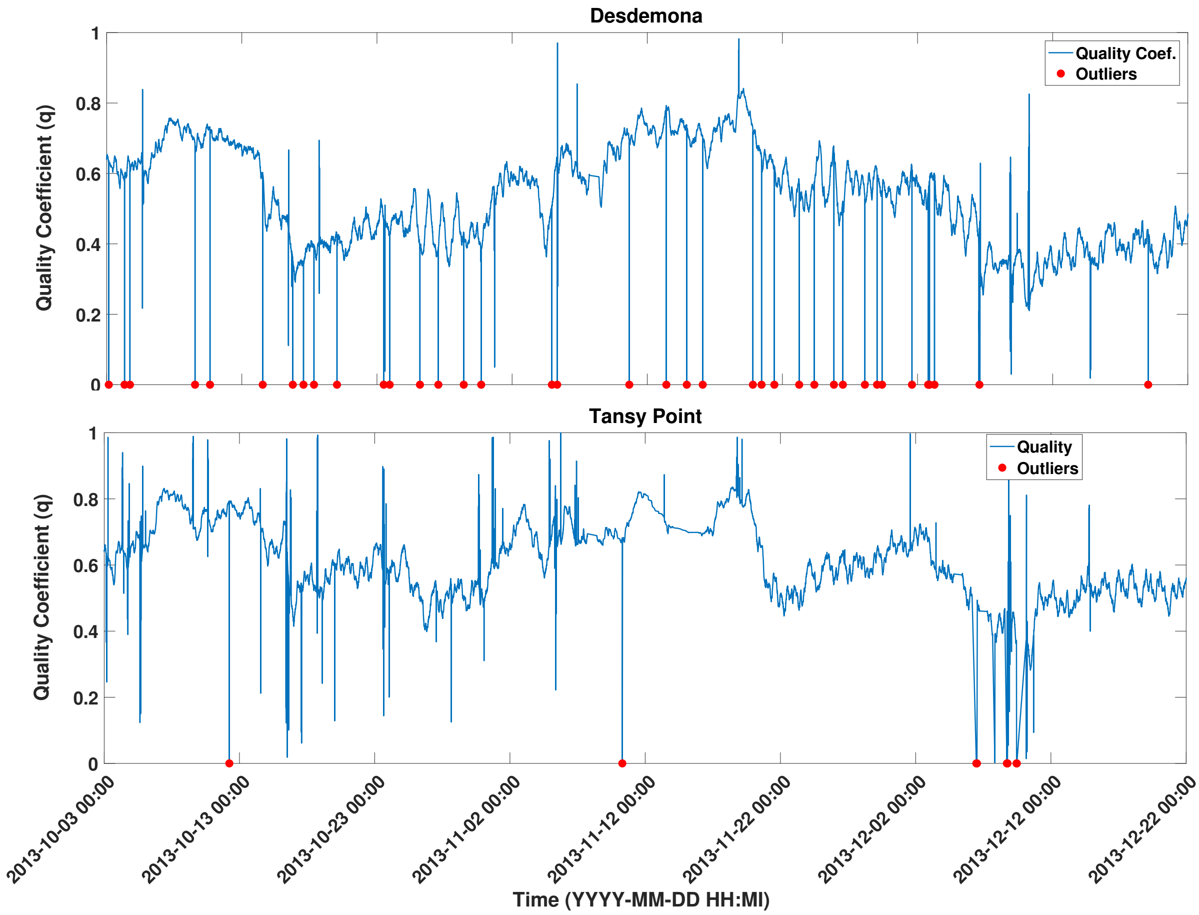

Figure 5.9: QE output.

The Measurement Reassessment (MR) block replaces the measurement m that is considered an outlier by a new estimated measurement m'. This is important because, in addition to the need of providing a correct value as the output of our solution, m (replaced by m') is used in the input vectors of the prediction models.

To evaluate the strategy for performing this estimation (see Equation 5.6) we tested against two other strategies that are intuitively worse. In fact, one of these strategies (named "No MR") simply keeps m without replacing it. The interest of considering this strategy it to allow us to observe the extent of the negative impact of using outliers to feed further predictions. The other strategy (named "Neighbors only") replaces m by the prediction that uses only the measurements of the neighbor sensors. The rational for this strategy is that the outlier can be an indication that the sensor producing it is faulty and hence, it does not make sense to use past measurements of this sensor in the reassessment.

The results are presented in Table 5.2, providing the comparison considering the number of detected outliers using each strategy. The adopted strategy is referred to as "All Average", provided it is based on an average of all predictions in P.

Detected Outliers				
Stations	***Jetty A***	***Lower Sd***	***Desdemona***	***Tansy***
Real Outliers	*0*	*1*	*44*	*11*
No MR	16	18	39	24
Neighbors only	1	3	73	29
All Average	1	4	39	9

Table 5.2: Number of detected outliers for all sensors according to the MR strategy.

The results in Table 5.2 allow us to confirm the importance of replacing the faulty measurements with adequate measurements. Also, it shows that, for this testing dataset, the adopted "All Average" strategy used for the Measurement Reassessment block performs generally better than any of the other strategies. Both remaining strategies underperform in this application. We note also that the "Neighbors only" strategy that does not consider the predictions based on the target sensor, clearly underperforms in the datasets that contain more real outliers. Therefore, this strategy is not feasible for this application.

Furthermore, we display in Figure 5.10 the effect of the propagation of the errors (outliers) in the ANNs inputs, via past measurements, when a "No MR" strategy is considered. By comparing both figures 5.8 and 5.10, which depict the output of the outlier detection for Desdemona and Tansy Point sensors using the two different measurement reassessment strategies, we can observe that the number of false positive outliers increases when no replacement of the detected outlier happens. This is due to the accumulation of errors within the predictions, which are always based on past measurements. This is particularly observable in the periods following an outlier.

In terms of the adopted MR strategy output, Figure 5.11 shows the behavior of m' for both discussed target sensors. We can observe that the measurements detected as outliers disappear and are introduced in the past measurements (ANNs inputs) replaced by a new replacement measurement m'. When not detected, the observed measurement m is effectively used.

The behavior of m' (Figure 5.11) represents the output of the ANNODE solution after the detection and correction of the outliers for the selected sensors of the monitoring network.

With these overall results, highlighting the ability to output the corrected measurements removing all the detected outliers, we have shown that this methodology instantiation was successfully applied to the considered case study. Given that the testing dataset is representative of the typical situations that can happen on these complex environments,

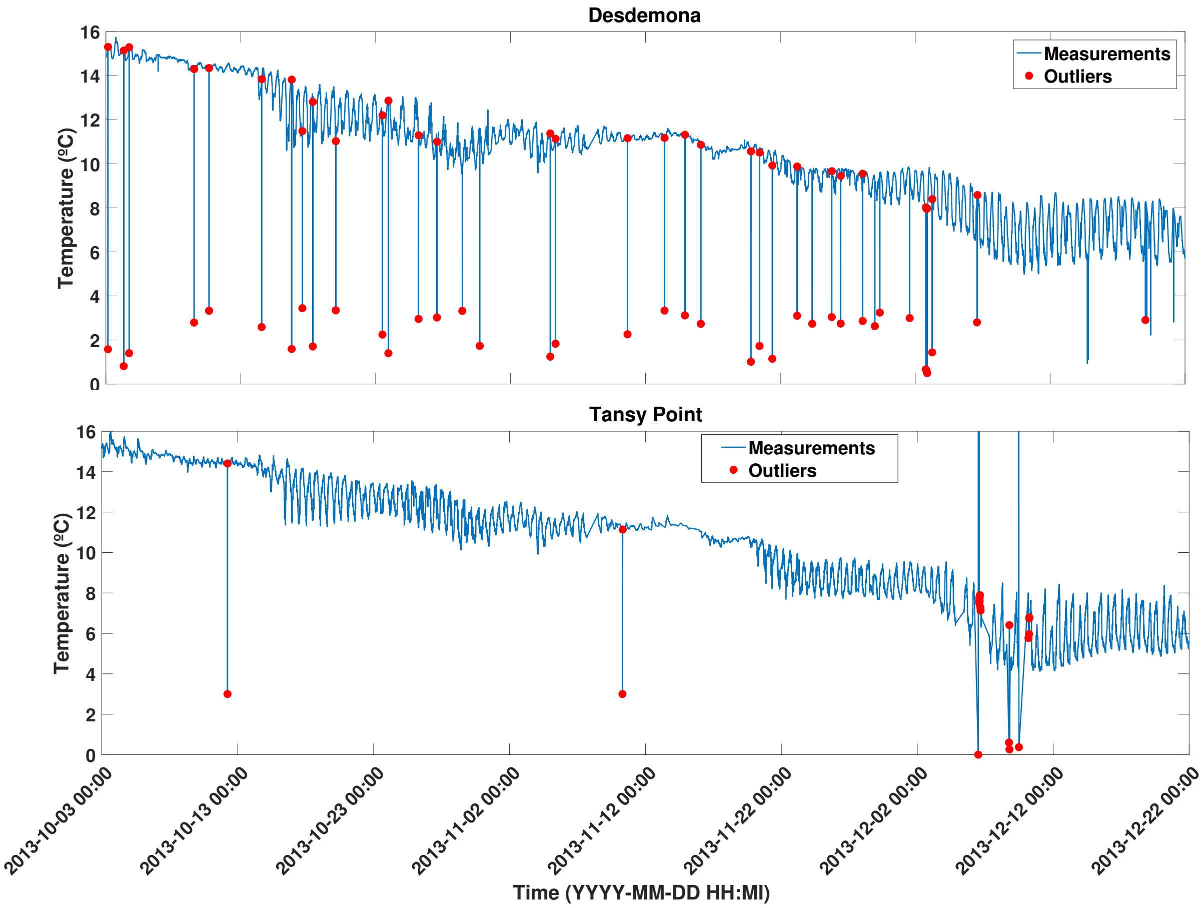

Figure 5.10: FD output without MR strategy.

we can generalize the conclusions for any aquatic monitoring network. Furthermore, although these results were obtained using existing datasets, it would have been possible to achieve the same accuracy results would we have applied the methodology in runtime. This is a major benefit that it brings.

5.4 Validation

In this section we perform a validation of the methodology and its instantiation to outliers (via ANNODE solution), via a comparison with other outlier detection techniques, using a common dataset, the Intel Berkeley Research Lab Mica2dot dataset [5].

The IntelLab dataset is a public collection of sensor data from a WSN deployed at Intel Berkeley Research Laboratory (University of Berkeley) consisting of 54 Mica2Dot sensor nodes measuring four types of weather variables during a period of 30 days, from February 28th until April 5th, 2004. The dataset includes light, temperature, humidity and voltage measurements, which were collected every 31 seconds.

To validate the methodology and proposed strategies, a comparative study is con-

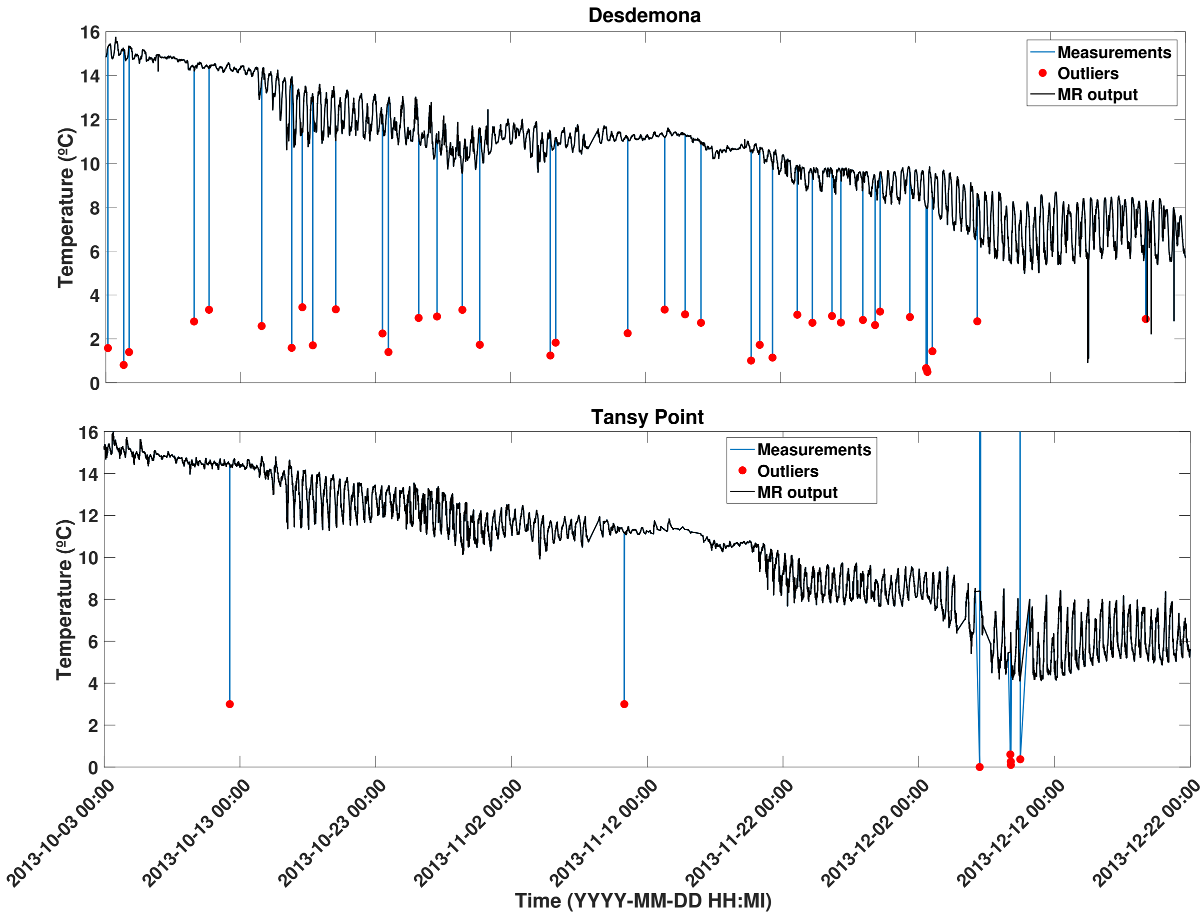

Figure 5.11: MR output for sensors Desdemona and Tansy Point.

ducted with selected state-of-the-art solutions that were also applied using the IntelLab dataset. To enable accurate comparisons, all solutions compared herein used the same subset of data from the IntelLab dataset, according to the experiments in [142]. Considering the used subset, since there is an absence of ground truth relative to the presence of outliers, artificial anomalies were injected in the subset of three nodes (N8, N9 and N10) of the IntelLab deployment. The comparison is then performed by measuring the effectiveness of the ANNODE solution presented in this thesis, for the detection of the injected outliers, with three other approaches already tested using the same subset with the same strategy of artificial anomaly injection.

As presented in [142] for the specific evaluation of the PCCAD (Principal Component Classifier based Anomaly Detection) technique, the same 150 samples of IntelLab dataset were extracted, using the temperature, humidity and voltage values of nodes N8, N9 and N10 to comprise the D1, D2 and D3 samples respectively. After the data extraction, a random injection of outliers/anomalies process was performed. This involved the fitting of the 150 samples to a normal distribution followed by an injection of 100 random artificial outliers generated according to the respective normal distribution, which replaced 100 of the 150 samples. We note that with this generation process, an outlier can end up having exactly the same value as the measurement it is replacing, which makes it impossible to be detected.

Table 5.3 shows values for the mean and standard deviation (StDev) in the distribution of the samples, regarding both the clean (without outliers) and the samples with injected random outliers. It is possible to conclude that the injected outliers barely affected the mean and standard deviation.

Dataset	**Variable**	**Clean**		**With Outliers**	
		Mean	**StDev**	**Mean**	**StDev**
D1	Temperature	20.641	1.616	20.549	1.631
	Humidity	36.609	1.553	36.757	1.593
	Voltage	2.70281	0.01697	2.70131	0.01745
D2	Temperature	20.796	1.633	20.688	1.674
	Humidity	37.345	1.645	37.452	1.661
	Voltage	2.77273	0.01682	2.77201	0.0172
D3	Temperature	20.534	1,571	20.429	1.601
	Humidity	37.96	1.503	38.066	1.52
	Voltage	2.68971	0.01484	2.68956	0.01555

Table 5.3: Normal Distributions of the experimental datasets.

To evaluate the ANNODE solution, we compare its performance against the three solutions in [142], which are the following:

- PCCAD model [142] – the Principal Component Classifier based Anomaly Detection model is centred on an unsupervised Principal Component Classifier split the offline training phase and the online anomaly detection phase whenever a sensor reads a new measurement;

- QS-OCSVM model [141; 186; 192] – the Quarter-sphere One Class Support Vector Machine is based on SVM classifier that makes use of sphere geometry to solve the quadratic optimization problem in the SVM formulation;

- H-OCSVM model [141; 186; 192] – the Hyper-plan One Class Support Vector Machine classifier differs from the previous model in the use of the plane geometry to solve the quadratic optimization problem.

In all techniques, including ANNODE, the detection problem comprises a training offline phase and an online detection phase, without the requirement of labelled data, used for the establishment of the ground-truth in similar problems. The metrics used in the comparison were the detection rate (DR), the detection accuracy, and the false positive rate (FPR).

In the comparison process, considering the random nature of the outlier injection process, the experiments were repeated 15 times as it was done in [142] for each of the three techniques and for each dataset (D1, D2 and D3). A single result for each metric (DR, FPR and Accuracy) was obtained by averaging out the results from those 15 runs. For each run, the training dataset remained the same, whereas the testing set, which included the random outliers, was different every time. Table 5.4 provides the evaluation results, showing average values for detection rate (DR), false positive rate (FPR) and accuracy achieved by ANNODE and the other three techniques, for each dataset.

Dataset	Metric	ANNODE	PCCAD	H-OCSVM	QS-OCSVM
D1	DR	95.42%	98.00%	94.80%	64.47%
	FPR	6.17%	3.60%	33.47%	12.77%
	Accuracy	**93.83%**	96.40%	66.53%	87.23%
D2	DR	95.16%	92.13%	97.13%	62.00%
	FPR	6.76%	9.91%	35.24%	13.95%
	Accuracy	**93.24%**	90.09%	64.76%	86.05%
D3	DR	92.27%	95.33%	97.80%	68.73%
	FPR	5.16%	5.78%	34.80%	10.51%
	Accuracy	**94.84%**	94.22%	65.20%	89.49%

Table 5.4: Comparison between ANNODE and other approaches.

The results presented in Table 5.4 primarily validate the use of ANNODE for a generic WSN dataset, with a high detection rate for all datasets and a low false positive rate. Also, the provided results show that the solution works consistently for all three datasets with approximately the same accuracy across the board (approximately 94%), whereas the other techniques present a more varying performance. Another observable outcome is the inferior DR on the D3 dataset comparing with the two other datasets, which can be explained by verifying Table 5.3 and confirming that the D3 dataset has a distribution more populated around its mean values, for all variables.

On the instantiation part of the methodology building blocks, in the Prediction block, all neural networks were trained with the same structure used in the previous section for the SATURN case study. In the Failure Detection block, the statistical technique was chosen again, being the comparison threshold adjusted for the best DR/FPR ratio possible, thus the stable accuracy shown in Table 5.4.

In terms of comparison results, it suggests that ANNODE outperforms both SVM-based techniques, exceptions are the DRs of H-OCSVM in D2 and D3 but presenting also high FPRs in those datasets. By comparing the results of PCCAD technique with

ANNODE, it is less obvious which of them is the best for the IntelLab dataset. Results show that PCCAD outperforms ANNODE in D1 but underperforms in D2. On the other hand, in D3, PCCAD presents a better DR than ANNODE, but produces worse results in terms of FPR and Accuracy. In conclusion, and knowing that the three techniques considered in [142] are among the best ones existing in the literature, ANNODE performs at least as well as the best of them for a dataset such as IntelLab.

5.5 Summary

In this chapter, the methodology for dependable monitoring in environmental sensor networks was instantiated to two different datasets, by selecting specific machine learning techniques to implement the procedures in the methodology building blocks overviewed in Chapter 4.

The ANNODE solution for the SATURN case study resulted from modeling the sensors next measurement through ANNs, by learning the spatiotemporal correlations between the target sensor and its neighbors. Also, the failure detection mechanism (FD block) was conceived by making use of a statistical technique to support the evaluation of a set of conditions. Lastly, the ANNODE solution also incorporates strategies to implement the QE and MR blocks, which are proven important for the detection and correction of outliers.

We evaluated the proposed methodology and the related ANNODE solution by applying it for outlier detection in a real dataset from an aquatic monitoring system. The application results provided a high detection percentage of the outliers existent in the dataset, which proves the effectiveness of the ANNODE solution when applied to a harsh environment.

Finally, ANNODE was validated by comparing it with three other outlier detection solutions, using the same dataset with artificially injected outliers. The comparison results prove that the ANNODE solution is at least as effective as other machine learning solutions for the detection of outliers in controlled environments, such as the IntelLab network.

Chapter 6

Offset and drifting failures detection

6.1 Introduction

Differently from outliers, offsets and drifts are characterized by a systematic failure behavior observed during a determined time interval. These are normally observable when a sensor is functioning during a long period of time without intervention, posing ultimately data quality issues.

Failures such as drifts and offsets are usually related either with environmental factors or to the sensor inner processes errors. Both scenarios can be prevented or ultimately mitigated with periodic calibration of the sensors. This calibration process is based on an adjustment of the sensor to the specifics of the environment and other external factors.

Although faults in sensor networks have been covered exhaustively in the specialized literature, the majority of the studies is dedicated to communication faults or outliers derived from sensor faults. In fact, detection and mitigation techniques for drifts and offsets in the context of sensor networks have not been addressed thoroughly, as we demonstrate in the next section.

In this chapter we instantiate the methodology proposed in Chapter 4, but now accounting only for faults related to drifts and offsets. The instantiation is directed to the SATURN case study, which we have adopted in this work. It comprises the definition of specific strategies for the FD block, still using the ANNODE machine learning techniques for the Prediction block.

This instantiation of the methodology is a particular solution for dependable monitoring in aquatic environments, with datasets containing systematic errors. This is performed with real datasets from sensors measuring the water temperature, injected with drift and offset failure scenarios. Moreover, the procedures and techniques of the instantiation are customized specifically for failures that show a persistent behavior over a time interval, contrasting with the spurious failures scenario (outliers for instance) presented in the previous chapter.

In Section 6.2, related work on mechanisms and techniques for detecting offsets and drifts, including the use of data fusion strategies, is reviewed, focusing on the particular situations involving sensor networks. A concrete instantiation of the methodology presented in Chapter 4 is then provided in Section 6.3. Limitations and further assumptions required to the application for drifts and offsets detection, in a real sensor data collected from a river-estuary aquatic system, are detailed and considered herein. Moreover, a concrete strategy to implement the Failure Detection block is provided and demonstrated to be effective. Finally, Section 6.4 summarizes the chapter.

6.2 Related work

In what concerns detection and correction methods for drifting and offset failure behaviors in sensor devices, there is a separation from single device and multiple devices (network). In the first category, we discuss calibration and its variants as a process to prevent and correct such failures. In contrast, in a multi-sensor situation it is possible to use data fusion techniques in order to detect and correct drifts and offsets.

The re-calibration process of sensors is usually performed off-field by removing the sensor of the monitoring environment and recalibrating it in controlled conditions, with potential data loss if no redundant way of collecting sensor data is available (and the added re-deployment costs).

Although sensor calibration may be sometimes a costly operation, given its frequency, it is necessary to assure the good quality of data. In order to minimize the number of interventions in the sensor, there are two alternative procedures. First, instead of the manual calibration before deployment, a factory setting or calibration is possible, with the advantage of reducing the time consumption efforts of the initial process, but not completely eliminating the problems related to the external factors involved. Also, another possible alternative is the auto or self-calibration, which is a software-based procedure to enable sensors to monitor themselves and self-calibrate using a reference. This latter option, being adaptive, is potentially better to deal with varied and even unpredicted circumstances, and is also designated as measurand reconstruction or sensor compensation.

The auto-calibration process is referred to the methods aimed at diminishing the effect of the disturbing parameters in input/output features of sensors, where the transduced value must have a direct relation with the measurand. The sensor becomes less sensible to past information, interfering environmental factors and noise. This is possible via numerical techniques that compensate the disturbances. These techniques are applied after the transformed signal being quantified, through digital signal processing. This method has been used with relative success, for instance exploiting statistical regression based on a priori knowledge [179] or using artificial neural networks [134; 146].

For the multi-sensor scenario, particularly in the context of sensor networks, these automatic calibration techniques have also been studied to correct drifts and offsets failures. However, these techniques only consider blind calibration, which means that there are no detection mechanisms for data faults. One of the first works is presented in [44], where the authors designed an algorithm to be used in high-density sensor networks in a post-deployment phase. This algorithm uses temporal correlations between pairs of neighbor sensors to correct their signal (measurements). An additional phase is explained as an optimization step by dealing with groups or clusters of sensor nodes. Another work [34] deals with blind calibration in sensor networks softening the high-density requirement, assuming a linear model for the sensor calibration functions, meaning that sensor readings are calibrated up to an unknown gain and offset for each sensor. They too rely on sensor correlations to model their behavior. In fact, data fusion is a common subject in blind calibration studies (more in [68; 169; 175]).

For the sensor networks scenario, there is a limited number of studies considering both detection and correction mechanisms of offset and drifts failures. Offsets analyses are more common than drifting ones, in particular in applications related to digital imagery. One exception is [176], where the authors present a machine learning approach to detect faults in WSNs. Their method consists in using Hidden Markov Models to capture both the dynamics of the environment and the dynamics of the faults. The authors also present an analysis on the extracted models to determine the types of faults (including offsets) affecting the sensor measurements.

Concerning specifically to drifting failures, a research group presented several studies over the last years regarding a design and its various improvements of a drift-aware sensor network [111; 112; 143; 162; 163; 164; 165; 166; 167; 168]. The original study presented the concept of a mechanism to detect and correct drifts in sensor networks. Afterwards, several data fusion techniques were introduced and demonstrated to be efficient. The group used statistical techniques, Kalman filters, Interacting Multiple Model algorithm, Recursive Bayesian algorithm, Spatial Kriging method, and ensembles of these techniques. Their work has been applied to high-density sensor networks measuring parameters such as temperature but also to image-related networks with geospatial information.

Lastly, focusing simply on the detection mechanism, among the many studies in the field of fault detection in WSNs, [184] presents a fault detection method for WSNs based on a multi-scale Principal Component Analysis (MSPCA). The study demonstrates the efficiency of the method in a laboratory network dataset detecting both offsets and drifts failures for temperature sensors.

6.3 Instantiation and results

Given the emphasis in this chapter on detecting and correcting drifts and offsets, a new instantiation of the proposed methodology is provided, focusing mainly on new strategies for the Failure Detection block (Section 4.3.3) and on the particularities of detecting systematic failure behaviors in sensors.

In Section 6.3.1, we review the case study dataset used for the demonstration, including the type of injected failures. The second subsection details the instantiation of the methodology, using machine learning for the modeling and prediction of the sensors behavior, based on data fusion concepts of the existent spatiotemporal correlations between sensors in the network. Similarly to Chapter 5, a statistical technique was used for the Failure Detection block.

In Section 6.3.3, the results obtained by applying the methodology and techniques to detect offsets and drifts in the case study dataset are presented and discussed.

6.3.1 Dataset and injected failures

The adaptation and instantiation of the methodology is evaluated using datasets from a public online environmental monitoring network, mentioned in this thesis as the SATURN case study, already introduced in Chapter 2.

The selected stations are the same as in the ANNODE solution (Chapter 5): Jetty A, Lower Sand Island light, Desdemona Sands light and Tansy Point. As explained, all these stations monitor similar variables and were operating simultaneously during the training and testing datasets. The training process, described further below, is split in two phases. The first phase includes the training of the prediction models and a second one is dedicated to the comparison method. The training dataset for the prediction models was the same as the one used for ANNODE, which is shown in Figure 5.1. The dataset to model the errors distributions that support the statistical technique was also the same as in ANNODE, and is shown in Figure 5.4. We note that these datasets encompass only correct behaviors of the sensors during a representative period of the monitored environment.

Differently from the outliers scenario in Chapter 5, we were unable to find any SATURN dataset relative to temperature or salinity showing the presence of relevant drifting or offset situations. An example of a drift failure in a SATURN dataset is shown in Figure 3.5. However, this example was taken from [15] and was found by experts from CMOP. While it is relatively easy for non experts to spot outliers, identifying drifts or offsets requires expert knowledge. We tried to obtain the dataset where this identified drift was found, but it was not publicly available. Therefore, for the evaluation of the instantiation herein, it was necessary to promote the injection of both failure scenarios in the testing dataset comprising temperature readings from 2010-10-02 until 2010-10-05 (see Figure 6.1). We define below the typical offset and drift scenarios to provide context to the failure injection in Section 6.3.3.

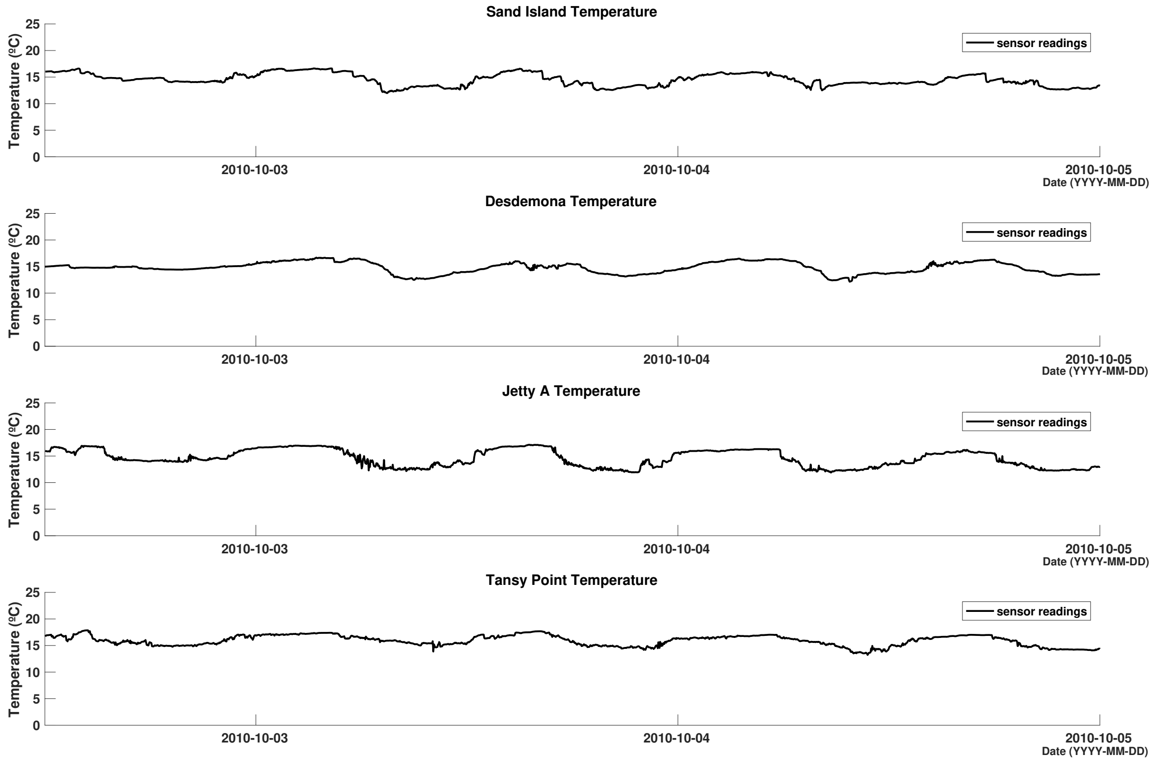

Figure 6.1: Testing dataset.

The offset failures can be characterized by a period of time during which the measurements exhibit a given offset, constant or almost with no variance, with respect to the expected sensor readings. On the drift failures, the drifting behaviors can be split into two categories related to their general pattern. A drift can be characterized by a smooth and slowly decay or growth, as in a linear or exponential function, represented in Figure 6.2a. The second category describes a drift also with a linear or exponential decay or growth but presenting discontinuities or sudden surges, abrupt changes or accentuated peaks, represented in Figure 6.2b. Additionally, regarding offsets and drifting failures signals, we presented examples of the respective polynomial expressions in Section 4.2.1.

For the evaluation performed ahead, several levels of intensity or deviation from the expected measurements were considered when injecting offsets and drifts.

(a) Examples of smooth drifts. (b) Examples of drifts with sudden changes

Figure 6.2: Categories of Drifting failures.

6.3.2 Systematic failures solution

For the instantiation of the proposed methodology to the detection and correction of systematic failures such as drifts and offsets, the same techniques as the ones presented in Chapter 5 for the outlier setup strategy (ANNODE) are followed, namely the artificial neural networks (ANNs) and statistical techniques respectively used in the Prediction and Failure Detection blocks of the methodology (Section 4.3.3). However, since there are notorious differences between spurious and systematic errors, these have implications on the strategies for Prediction and Failure Detection. These implications will be detailed in the following subsections.

Prediction block

As mentioned, there are three steps required to prepare the instantiation of the methodology to a monitoring environment dataset. The initial step is the selection of the network sensor nodes that are highly likely to be correlated. This correlation can be verified by considering either the physical distance or through expert knowledge of the specific environment dynamics. The second step is the selection of the data fusion techniques for the Prediction (P) block, considering that such techniques must be adequate to resolve the estimation problem (predicting the target sensor next measurement). Finally, the third step includes the selection of the specific datasets for the training process (if required) of the chosen techniques. Therefore, these datasets contain correlated timeseries data comprising the sensor measurements that characterize the sensors behavior and, if existent, other important related information.

The sensors selection was presented in the case study dataset description (Chapter 2, Section 2.5), whereas the training datasets and selected data fusion techniques were discussed in detail in the previous chapter, Section 5.3.1. For the modeling of the sensors behavior and its future measurements, several ANNs were selected and trained. In terms of ANNs options, the choices about the structure and learning algorithms taken previously were maintained, using feedforward ANNs (multilayer perceptron) consisting of two hidden layers, with each neuron capacitated with a hyperbolic tangent sigmoid (*tansig*) activation function, trained via Levenberg-Marquardt method. All ANNs were implemented and trained using MATLAB *fitnet* function (Deep Learning toolbox).

In Chapter 5, we defined the type and structure of ANNs to use for the datasets of the case study, in which for monitoring measurements of a given target sensor, the inputs are comprised of the vectors with an history of measurements of the neighbor sensors and possibly of the target sensor itself, characterized in Equation 5.1 by U.

In terms of the predictions provided by the ANNs (P block), there is a clear difference between outlier and systematic detection. With the outliers, as shown in Chapter 5, we consider three types of prediction models: using only past measurements information from the target sensor, using only measurements from the neighbor sensors and using past measurements from both target and neighbors. For systematic failures detection, given that we have failure behaviors that may not vary abruptly as an outlier and affect systematically the target sensor measurements, in the prediction models we can not consider predictions based on the target past measurements. Consequently, we only consider here ANNs trained based on the measurements of the neighbor sensors. Therefore, we discard past measurements from the target sensor because these have a strong influence in the predictions and would lead to wrong predictions. In case of a drift, using past measurements would lead to predicted values that are never far from the current measurements. Additionally, in case of an offset, the first measurement affected by the offset could be perceived as an outlier but the subsequent measurements, being also affected by the offset, would be close to a predicted value based on the history. Therefore, there is no point in using past measurements of the target sensor.

One important difference between systematic and spurious errors is that the former are observed over time while the latter are observed in a single measurement. Therefore, systematic errors can not be detected as soon as they start, only after being observed for a certain time interval. This, however, has to do with the Failure Detection strategy and will be addressed ahead.

Additionally, given the possibility of environmental events situations, which affect several sensors and their respective measurements, it will be necessary to build multiple prediction models involving different sets of neighbor sensors, with the objective of distinguish these event situations from failures of the target sensor. Further details are provided ahead.

For systematic errors detection, since prediction models are built only using neighbor sensors measurements, having a single neighbor only provides a single prediction model. Therefore, the assumption that the system minimum size is two, which was made in Section 4.3.1, must be revised. Herein, we assume that the sensor network is of size N

with $N > 2$ (including the target sensor). This assumption makes it feasible to create prediction models not only to detect the systematic errors but also to distinguish them from most environmental-related events and determine which of the sensor is drifting.

The construction of the prediction models in this instantiation, considering the choice of ANNs as a data fusion technique for this application and the need to have multiple prediction models, is done based on sets of sensors combining different neighbors. For instance, we consider here a network of N sensors where $N = \{w, x, y, z\}$ is a set of the 4 sensors $\{w, x, y, z\}$, analogous to the case study. Considering that no virtual sensors exist to complement this set and that the past measurements of target sensor are not used, if the target is w, seven ANN models can be generated as shown in Figure 6.3.

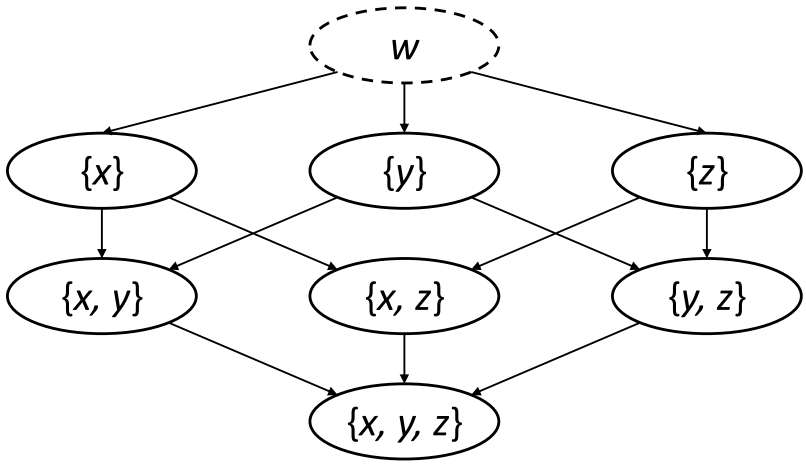

Figure 6.3: Prediction subsets of a network, for a target sensor w.

Consequently, for this instantiation, given that we constructed the prediction models for each target sensor of the network (sensors Jetty A, Lower Sandy, Desdemona and Tansy Point), a total of 28 ANNs were trained.

One constraint of the prediction models that are based only on partial set of neighbors, is the possible loss of accuracy in the estimations (e.g.,$\{x\}$, $\{x, z\}$, $\{y, z\}$) when compared to the prediction model based on all neighbors ($\{x, y, z\}$). This potential problem is mitigated because we constructed several of these prediction models, which allows for a consensus based criteria to be applied when reasoning about the existence of failures. This will be explained next.

Failure Detection block

In the Failure Detection (FD) block, similarly to the ANNODE solution, we used the statistical technique as a comparison method, in order to calculate the differences between the measurement m and the corresponding predictions provided by the Prediction block (P).

This statistical technique, as described in Section 5.3.2, uses a training dataset to learn the probability distributions fittings (implemented in MATLAB using *fitdist* function) between the errors of the prediction models defined in P and the expected measurements. Using the training dataset described in Section 5.3.2, the square errors between measurement m and each prediction p of P (Equation 5.2) are obtained and we are able to obtain the final cumulative density function (CDF). This CDF allows us to calculate the probability of the error between current target sensor reading m and prediction p. Therefore, by defining a threshold for error probability, we can assess the significance of the observed differences between the measurement m and the predictions p in P.

In this instantiation for the detection of systematic errors, we have different detection conditions from those formulated in ANNODE. Firstly, each measurement of the target sensor is compared with the seven predictions and the number of significant differences, which can be between zero and seven, is recorded. Then, these differences are evaluated over a significant temporal window to perform the intended detection of systematic failure.

To provide an intuition on the proposed approach, let us reason about possible situations and their implications on the number of significant differences. If the target sensor is being affected by a failure, one will expect that all the prediction models will provide values that are significantly different from the measured one. Therefore, if this happens over a period of time, this will be a clear indication that the sensor is subject to a drift or offset failure. On the other hand, it is possible that an event is affecting all the neighbor sensors. In this case, it is likely that the measurement will also be significantly different from all predictions. Therefore, from the perspective of significant differences, this case is indistinguishable from the former one. The target sensor will be considered faulty, which would be justifiable because it is the only not affected by the event. Nevertheless, we note that this situation is very unlikely in reality because events have typically a localized effect and thus not all neighbor sensors would be affected. In the case of events with a wide geographical span (e.g., a haze storm) all sensors including the target one will be affected and hence no failure will be detected.

There are a number of intermediate situations that may be categorized in two groups: (a) a single neighbor sensor is faulty or (b) an event affects a subset of the neighbors (for the case of $N = 4$, this subset must have two neighbors). In all these cases, the target measurement may be significantly different from some predictions, but not from all. Therefore, if we require that all differences are significant, the target measurement will never be considered faulty.

For this systematic detection, a temporal window must be defined so we can distinguish single point situations from systematic failures or even from an environment-related event. These single point situations can be spurious errors or just regular fluctuations in the differences between measurement m and the corresponding predictions p, in which the difference can be significant for that instant but not in a systematic manner. This temporal window will allow us to characterize correctly a systematic failure, either being an offset or a drift.

The temporal window will have size T time units, which is typically defined by the application and related with the required failure detection latency. The rule of thumb is that the window must include enough measurements to characterize the temporal scales of relevance with enough resolution for the phenomena at stake, depending also on the frequency of sensor measurements. The number of measurements in the window, k, must be at least $k = 3$, such that it is possible to conclude that a certain behaviour is systematic, but k can be made larger as this will allow to achieve more precise conclusions.

Therefore, for each new measurement of the target sensor a history of k measurements within the window T will be verified. This history of measurements is represented in Figure 6.4 for two instances of hypothetical windows of size T at time instant t and $t+1$, considering the target sensor w. The first instance is highlighted with the solid line in the bottom, whereas the second is the dashed one.

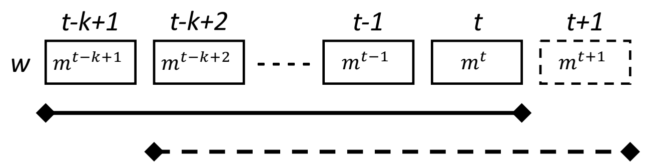

Figure 6.4: Examples of windows of size k for sensor w.

The proposed approach for the detection of systematic failures is presented in Algorithm 1.

The objective of the function defined by the Algorithm 1 is to detect a systematic failure affecting the target sensor. For that, the procedure takes as input a window W containing k measurements of the target sensor and the set of prediction models relative to this target sensor. The procedure works as follows. It takes a measurement m and determines its similarity with each of the predictions for m provided by the n prediction models. Every prediction that is not similar to m is counted and recorded in the differences vector D. After iterating all measurements in the window, each of the k positions of D will contain the amount of differences, ranging from 0 to n. Whenever these differences equal n, they are counted as sensor faults. If the total number of detected faulty measurements is a majority in the window of size k, this is interpreted as a sufficient indication that the sensor is malfunctioning and providing measurements that are systematically deviating from the measurements of all its neigbours. We note that this majority does not need

Algorithm 1 Detection of systematic failures for one target sensor

W : measurement vector $\{m^0, m^1, \ldots, m^k\}$
P : all prediction models for the target sensor
D : differences vector for each m in W

```
function SystematicFailureDetection(W,P)
    k ← sizeof(W)
    n ← sizeof(P)
    i ← 0
    numberFaults ← 0
    for each m ∈ W do
        D[i] ← 0
        for each p ∈ P(m) do
            if ¬similar(m, p) then
                D[i] ← D[i] + 1
        i ← i + 1
    for each d ∈ D do
        if d = n then
            numberFaults ← numberFaults + 1
            if numberFaults > k/2 then return failure detected
return no failure detected
```

to be formed by a set of contiguous positions of D with maximal value. This allows to mitigate the possible lack of accuracy of prediction models and the fact that neighbour sensor measurements may be affected by noise or outliers, leading to predictions that end up being close to the target measurement, which is not detected as faulty.

Additionally, the following considerations about using this strategy can be issued:

- In the smooth drift scenarios it is particularly difficult to detect the failure of the faulty sensor, specially if we do not have sensor redundancy providing highly-correlated measurements. The windowed verification defined above allows for an adequately large window to be used in order to deal with these situations;

- The occurrence of short-term anomalies, namely sporadic outliers or short sequences of outliers that can be detected with the ANNODE solution, must be distinguished from systematic errors. The majority criteria considered for detecting a systematic failure allows to deal with this need.

We test this strategy for systematic failures detection in the next section, using the testing dataset presented in Figure 6.1 with artificial injection of failures.

Quality Evaluation block

The strategy used to implement the Quality Evaluation block is quite similar to the used in the ANNODE solution (Chapter 5). To evaluate the quality of each measurement, we use again Equation 5.5, which calculates the inverse of the average of the cumulative probabilities of each error, for m against all the predictions in P. Also, like previously done for the case of outlier failure detection, whenever a systematic failure is detected, the quality coefficient q is set to 0.

However, the detection of a systematic failure has a wider implication than the detection of an outlier. When a systematic failure is detected, this means that a majority of measurements in the considered temporal window is significantly different from their corresponding predictions. Therefore, even if the most recent measurement of this window would be assigned a good quality value by applying the Equation 5.5, there may still exist a majority of faulty measurements in the window. This means that the target sensor will be considered to be in a faulty state and the quality assigned to this measurement will still be 0. Only after a while, when faulty measurements become a minority, the quality of new measurements will again be assigned through Equation 5.5.

Measurement Reassessment block

In the Measurement Reassessment (MR) block, a similar strategy to ANNODE can be adopted, where the average of all the available predictions in P is used, as expressed in the Equation 5.6. However, once again the fact that we are detecting a systematic failure has a wider implication than the detection of an outlier. In this case, because the failure is considered to span the measurements in the entire window, all these measurements must be reassessed. This is done to compensate for the fact that the detection of a systematic failure takes some time, until a majority of measurements is considered faulty. Some of these measurements, which had not been reassessed because there was not yet a detected failure, end up being reassessed when the failure is finally detected.

6.3.3 Application results

This section describes an experiment that was done with MATLAB to evaluate the described strategies for the detection and correction of measurements affected by systematic failures.

Considering that the case study dataset does not contain, for the selected sensors, any identified drifts or offset failures, both types of failure were artificially injected in one of the selected sensors dataset, namely in the Jetty A sensor dataset.

Concerning the injection of the offset failure, an artificial offset of $+2°C$ was introduced on all measurements starting on October 3^{th}, 2010 at 12 noon. This is illustrated in the top graph of Figure 6.5. Considering the typical variation of the temperature monitored by the studied sensors, the introduced offset was selected with the objective of being approximately half observed temperature range in the testing dataset.

With respect to an injection of a drift, we decided to introduce a linear deviation with a steady growth ranging from +0.01°C to +7°C, also starting from on October 3^{th}, 2010 at 12 noon (see bottom graph of Figure 6.5). Furthermore, this growth is effected at a rate of +0.01°C per measurement. Therefore, the final increase of +7°C is achieved after 700 measurements, corresponding to almost 24 hours for a 2 minutes measurement period.

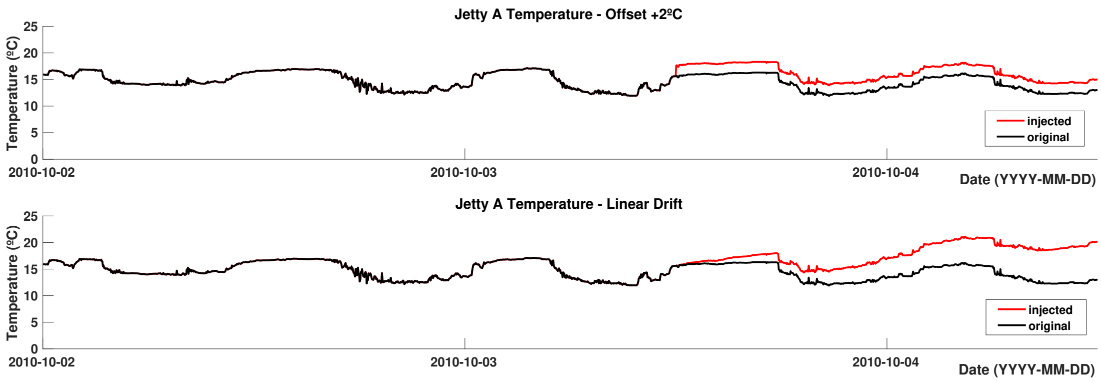

Figure 6.5: Offset +2°C and linear drift failures (injected).

The experiment was performed by training 28 ANNs for the Prediction block, as described in Section 6.3.1. In addition Algorithm 1 was also programmed in MATLAB.

To determine the size of window W, a temporal window T of 30 minutes was considered. Given that the dataset contains measurements obtained with a period of two minutes, the size of the window was set to $k = 15$. This also means that for the detection of a systematic failure, at least 8 measurements would have to be considered faulty.

Another parameter that we had to configure was the similarity threshold used for the comparison method applied to a measurement and the corresponding predictions in P ($similar(m, p)$ function in the Failure Detection block).

The concrete value used for this threshold determines the sensitivity of the similarity function to differences between a measurement and a prediction. A low threshold implies a higher sensitivity to these differences and hence a higher probability that failures due to deviations are detected (as well as false positives when predictions are affected by errors). A high threshold implies the contrary, lower probability of failure detection and higher probability of false negatives. A problem is then to determine an adequate threshold. The problem can only be addressed and solved when considering a specific use case, because the threshold depends on the concrete measured variables, their values, their dynamics, etc.

Given a certain use case or dataset, a method to determine an appropriate threshold must be applied and this threshold can then be used throughout the lifetime of the monitoring system. This method consists in applying the monitoring solution to a controlled dataset, testing different thresholds and observing their impact on the number of false positives and false negatives. This controlled dataset must have some measurements which are known to be correct and some which are known to be faulty, for instance affected by a drift or an offset. The objective is to find the threshold that maximizes the accuracy of the faulty measurements detection.

In order to evaluate the proposed approach for systematic failure detection, while considering the already defined use case, we started by applying the method described above to find an appropriate threshold. Therefore, we applied the monitoring solution to the dataset in which the Jetty A sensor had an injected drift and we tested 50 different threshold values ranging from 0.50 to 1 in steps of 0.01. Initially we measured the number of false positives obtained for each of the threshold values (Figure 6.6). The results show that any threshold below 0.68 (or 68%) results in the false detection of a systematic failure. This should be the lowest value to be used for the threshold and it was the value that we used to configure the similarity function.

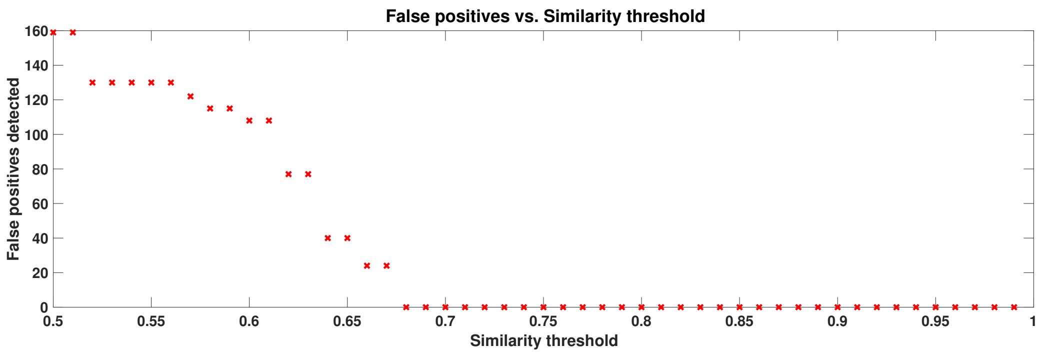

Figure 6.6: Number of false positives detected in a batch of 50 different thresholds.

This threshold of 0.68 triggers the detection of a failure when the measurement is affected by a deviation of +1.28°C with respect to the original value before injecting the drift failure. Clearly, any measurement affected by a higher deviation should also be detected as faulty, depending of course on the measurements of the neighbor sensors and the predictions based on them.

An higher threshold value can be used if the monitoring application only requires higher intensity deviations to be considered as failures. In other words, a small drift was acceptable for this application. The advantage of using a higher threshold is that it decreases the probability of false positives. In this case, the possibly higher number of false negatives is somewhat irrelevant.

Nevertheless, we determined the threshold values leading to increases of the number of false negatives, using the results obtained for determining the threshold. Table 6.1 provides these threshold values and the corresponding temperatures and number of false negatives. For instance, when the threshold is between 0.68 and 0.71, the drift detection is triggered at +1.28°C, corresponding to 127 false negatives. When the threshold becomes 0.72, the drift detection is only triggered at +1.35°C, meaning that at this point the number of false negatives increased to 134.

The false positive detection in this case is directly related to the drift detection timeline. With the threshold of 0.68 the drift is detected from moment it grows larger than +1.28°C, which happens at 4 hours and 16 minutes after the initial injection. With a threshold of 0.85 the failure is detected at +2.62°C, happening at 8 hours and 44 minutes after initial increment. This level of sensitivity analysis may be important, for example, in determining the related sensors maintenance operations timeframe.

Threshold	*0.68*	*0.72*	*0.74*	*0.75*	*0.76*	*0.79*	*0.85*
Drift	+1.28°C	+1.35°C	+1.43°C	+1.5°C	+1.58°C	+2.39°C	+2.62°C
False Negatives	127	134	142	149	157	238	261

Table 6.1: Drift detection evolution based on the threshold.

As already mentioned, we selected a threshold equal to 0.68. This threshold guarantees that no false positives are observed in the dataset containing the injected drift. In addition, when considering the dataset containing the injected offset of +2°C, the threshold is smaller than the one which would be required to be sensitive to this offset value (as derived from Table 6.1). Which is confirmed further ahead in the detection results.

Using a selected threshold of 0.68, we now provide the obtained results. We start by showing the output of the Failure Detection block, which are failure indications. Figure 6.7 shows the two datasets with the injected failures but in which the measurements detected as faulty are depicted in red.

From this figure, it is possible to conclude that all measurements affected by the injected offset are detected as faulty. A few measurements preceding the injection of the offset are also detected as faulty. This is because they are included in the window of which a majority of measurements is faulty. Concerning the drift, it is clear that some faulty measurements are not considered faulty. This is directly due to the fact that the threshold was selected to avoid false positives and hence leads to some false negatives. If a smaller threshold would be selected, then we would see some red points showing up in correct measurements before the point after which the fault was injected.

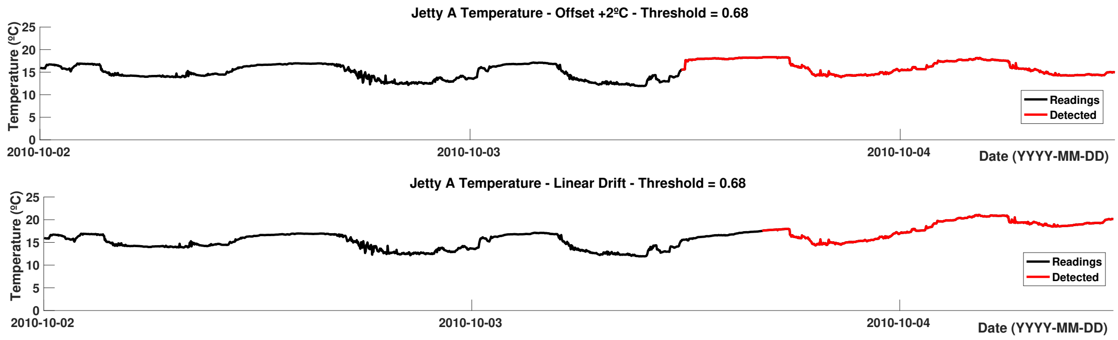

Figure 6.7: Detection of the failure scenarios.

For all the measurements identified as faulty by the Failure Detection block, the Measurement Reassessment (MR) block determines a replacement value. The objective to obtain corrected measurements which are close to the real ones. To evaluate if this indeed happened in our experiment, we depicted in Figure 6.8 both the original datasets for the Jetty A temperature sensor and the ones resulting from the application of the monitoring solution to the datasets with injected offset and drift failures.

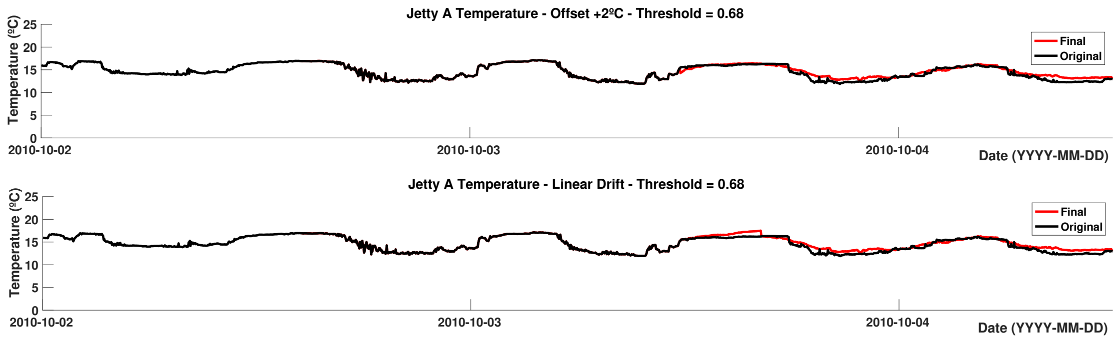

Figure 6.8: Final signal with MR outputs versus original dataset without failures injection.

In this figure, we can observe that although the corrected measurements do not fully correspond to the original ones, the resulting signal is quite alike the original one. In terms of the accuracy of the MR strategy, the root mean square error (RMSE) between the corrected measurements and the original target sensor signal considering only the portion of the datasets affect by the injected failure. In the injected offset failure scenario this RMSE was 0.46°C. Comparing with the 2°C RMSE that was affecting this part of the dataset, we can conclude that the improvement was significant. Concerning the injected drift failure scenario the obtained RMSE was 0.50°C. Comparing with the 4.14°C RMSE affecting the injected dataset, the improvement is even higher. The extent to which the replacement measurements will be close to the original ones depends on the correlation between the affected sensor and the neighbor sensors.

Finally, the Quality Evaluation (QE) block output in the failure scenarios, according to the strategy described in the previous section, will be 0 for all measurements detected as faulty and will be defined by Equation 5.5 for the remaining ones. In the latter case, the concrete quality values will depend, once again, on the correlation between the target sensor measurements and the measurements of its neighbor sensors.

6.4 Summary

In this chapter, the methodology for dependable monitoring in environmental sensor networks was instantiated to a case study dataset from SATURN monitoring network, for the detection and correction of systematic failures. This involved the selection and application of well-known machine learning techniques for the exploitation of the spatiotemporal correlations between subsets of neighbor sensors and the target sensor.

Therefore, the instantiation followed the proposed methodology with a Prediction block containing relevant prediction models for the next measurement of the target sensor, using several ANNs based only on the neighbors information. In the Failure Detection block, a strategy was delineated that verifies within a window comprising the current and past measurements if a detection criterion is met, using a statistical method that analyses the probability of the abnormality of the sensor reading, comparing it with the output of the predictions. Consequently, the MR strategy also considers the same window for determining the faulty measurements that need to reassessed and output the corresponding corrected values.

The solution was evaluated using the case study datasets, in which offset and drift failures were artificially injected. The results obtained by applying this instantiation of the monitoring solution allow to conclude that the adopted strategies are effective for the detection and correction of the systematic failures.

Chapter 7

Conclusions and future work considerations

7.1 Conclusions

This section presents the final conclusions regarding this thesis and the respective contributions to advance the state-of-the-art in the dependability of aquatic monitoring systems.

In this thesis we proposed a generic methodology for dependable monitoring in environmental sensor network, as well as concrete solutions for instantiating this methodology in realistic use cases. The highly dynamic nature of the monitored variables and the uncertain occurrence of events affecting the monitoring process constitute challenges to achieve confidence on the quality of collected data. Therefore, with the proposed methodology and instantiation techniques we aimed at addressing these challenges and achieving the following objectives:

1. The detection, categorization and correction of faulty measurements in environment monitoring sensor networks. Faults in such sensor networks have different origins and consequently affect sensors in different manners, producing different kinds of errors reflected in sensor measurements. Due to the multiple factors that may interfere in these monitoring networks, there is no well-defined process to automatically detect sensor failures and correct the consequent measurement errors through the estimation of appropriate replacement values. Additionally, existing solutions either do not consider the complexity of the monitored processes or do not contemplate all the typical failures that affect sensors in these often harsh environments.

2. The definition of solutions exploiting multiple forms of redundancy to mitigate the impact of external factors on the correct perception of the sensors' state and to allow the estimation of a correct ground-truth. Given the existence of environmental-related and impactful events, there is a need to distinguish them from sensor failures.

Generally, fault detection and correction solutions do not account for the possibility that apparently erroneous measurements maybe due to real events occurring in the monitored environment, which eventually may lead to false positive detection situations. Furthermore, typical solutions for data fusion are focused only on exploiting data provided by sensor nodes, without considering the possibility of using other forms of redundancy as provided by forecast models, acting as virtual sensors.

3. The definition of dependability-oriented solutions to automate the evaluation and correction of faulty measurements, providing a notion of data quality. The typical quality control procedures include a manual overview of the network datasets to analyze the existence of failures within those datasets. This requires expert-knowledge on the monitoring site and the network deployment. Furthermore, this manual process does not provide any quantitative indication on the resulting quality of the monitored data and is hence hardly appropriate from a dependability evaluation perspective.

The present work achieved all the proposed objectives by:

- Identifying and characterizing the existing solutions to achieve dependable monitoring in sensor networks. We did it through an analysis of the several types of faults that affect the sensors and network operation. Moreover, we enumerated the relevant strategies that support the mitigation of the effects of faults on sensor data and the relevant failure modes;

- Analyzing the effects of phenomena related to aquatic environments on the sensors deployed on those environments;

- Evaluating the appropriateness of different data fusion techniques for the modeling of sensors behavior, namely Kalman filters, Statistical fusion and Artificial Neural Networks (ANNs). The goal was to use these techniques to exploit all the existing spatiotemporal correlations between sensors within a sensor network. Also, we studied the use of virtual sensors, based on environment-specific and complex computational models, as an additional redundancy strategy to improve the data fusion results;

- Designing a dependable data quality oriented methodology for the definition of environmental monitoring systems. The goal of this methodology is the provision of building blocks with different purposes. The concrete implementations of the building blocks can be done through the definition and application of the respective strategies based on machine learning techniques. Ultimately, these strategies exploit the existing correlations between the sensors of the sensor network to provide knowledge of, and to improve the overall data quality provided by the monitoring system;

- Evaluating the proposed methodology through its instantiation and application to specific monitoring systems. We instantiated the methodology considering concrete use cases and respective datasets, in particular using datasets from the SATURN case study and using the IntelLab dataset. Moreover, the evaluation was performed considering the detection and correction of outliers, offsets and drift failures in the datasets;

- Validating the outlier detection instantiation, named ANNODE. It was instantiated according to the proposed methodology, based on machine learning data fusion, in particular using artificial neural networks. This validation was done by comparing our solution against three state-of-the-art techniques for the outlier detection in the publicly available IntelLab dataset. The ANNODE solution performed at least as well as the best of the other techniques.

In conclusion, the presented work, which addressed the need for automated dependability-oriented solutions to aquatic monitoring systems in environments affected by external factors, provides the following contributions as an advance to the state-of-the-art:

- The effective detection of spurious and systematic failure modes considering a new generically applicable methodology to environment monitoring systems, able to deal with the highly dynamic characteristics of the monitored variables and the possible occurrence of unpredictable external phenomena. As demonstrated, although there are several works on the fault detection subject, these are mainly focused on outliers whereas the other types of failures tend to be ignored or are dealt with lightly. In this thesis, we enable the detection and correction of sensor faults affecting sensor measurements with the support of the proposed methodology and concrete strategies based on machine-learning techniques to implementing its building blocks;

- The inclusion of environment-related information in the sensor data fusion techniques, in order to improve the overall fusion process. Existing approaches ignore this type of information, using mainly the sensor measurements and its inherent correlations. With available complex computational models that produce relevant environment-specific simulations, we are able to characterize which are the neighbor sensors that offer a better correlation with the target sensor and thus extract additional information to support the distinction between events and failures. Furthermore, we proposed in this thesis specific strategies using fusion approaches that not only exploit the spatiotemporal correlations existent between the physical sensors but also are capable of using the external information, from the forecast models, as virtual sensors, providing an additional source of redundancy and hence improve the fusion results;

- The estimation and provision of a data quality quantitive indication for each new measurement, by defining a quality coefficient that reflects the sensor state. Typically, failure detection and correction solutions do not provide any such indication of the measurement quality. In the proposed methodology, the quality coefficient is determined for each new measurement based on the strategies used to detect and correct failures, considering not only their outcome but also additional information regarding the sensors performance, including in particular if there is any failure affecting its measurements.

7.2 Future work considerations

The research performed in this thesis can be further developed in several directions, of which we identify and describe five main ones::

1. Evaluation of the proposed dependability-oriented methodology and developed strategies for prediction, failure detection and measurement reassessment in other scenarios featuring different datasets (containing monitored variables with different characteristics), and considering other types of failures;

2. Development of a software tool to support an easy instantiation of the methodology to already deployed and working sensor networks;

3. Study of the feasibility and performance of strategies based on different machine learning techniques, namely for the Prediction and the Failure Detection blocks;

4. Generalization of the Failure Detection strategies to any number of nodes in the sensor network;

5. Definition of improved strategies for implementing the Quality Evaluation block

In the following paragraphs we describe these directions in more detail.

Different datasets and types of failures

In Chapter 4, we proposed a methodology that can be generically applicable to monitoring systems subject to harsh and highly dynamic environmental conditions, based on data fusion techniques to explore spatiotemporal correlations between the sensor network nodes. We successfully validated the generality of the methodology against two different real sensor networks datasets. However, the successful instantiation of the methodology, with specific configurations of the strategies implementing each block, is highly dependent on the selection of configuration parameters adapted to the characteristics of the monitored variables and the environmental processes. Therefore, it will be interesting to evaluate the extent to which the proposed approaches can be applied in other, possibly very different, application scenarios, and how they perform in comparison to existing solutions specifically designed for monitoring in those scenarios. In this thesis, we were limited on the selected sensor types (water temperature and salinity) due to the required representativity and subsequent necessity of sensor datasets in the same monitoring period. A further analysis on the prediction models and failure detection strategies should be considered, using other types of sensors datasets. In fact, environment monitoring networks are typically composed of an extended array of different types of sensors that monitor a plurality of physical and biogeochemical parameters, in different monitoring frequencies and monitoring conditions (height or depth for instance).

The generality of the proposed methodology should also be further validated by considering additional failure modes and defining corresponding detection and measurement reassessment strategies. In concrete, in this thesis we did not focus on the detection of noise, crash or jammed and trimming failures. Crash failures should be easy to handle, in particular by exploiting the fact that in most cases data are collected in a periodic way, which allows for timers to be set up in order to detect the lack of some measurement after the defined period, and exploiting correlated sensors to determine replacement measurement. Concerning noise, the deployment of signal processing solutions applied to histories of measurements may be a viable approach to be applied as a strategy for measurement reassessment, which can be investigated in future work. Finally, trimming failures have some similarities with offset and drift failures and hence the already proposed solutions for the detection of systematic failures is likely appropriate to also handle this kind of failures.

Lastly, in the context of the presented solutions (chapters 5 and 6), we did not address an evaluation in datasets containing both types of errors, spurious and systematic. The performed experiments for the implemented solutions, comprising each of the four methodology building blocks, were successfully performed separately and resulted in corrected measurements whenever the failure is detected. The simultaneous use of both solutions implies the existence of methods to output a single quality coefficient q for each measurement and a single corrected measurement whenever the two categories of errors are simultaneously detected. The definition of these methods and the evaluation of their merits constitutes further work that should be done.

Software tool

In chapters 5 and 6, we described all the required steps to implement each of the building blocks of the methodology. The application of these steps to any given sensor network dataset may not be straightforward for every user and requires some transversal background knowledge. Configuring system parameters to achieve an optimal performance requires some understanding of concepts related to machine learning and to dependability, in addition to knowledge about the characteristic of the monitored environment and their impact on these configuration parameters. In fact, this knowledge is necessary not only for configuring system parameters, but also to instantiate the multiple blocks in a convenient way. For instance, to instantiate the Prediction block it is necessary to select sets of correlated sensors (to obtain sufficient redundancy, without introducing noise), select appropriate training data (representing, as completely as possible, the correct behavior of the monitored variables), and perform the actual training of the neural networks. Therefore, for practical reasons, it would be important to develop solutions to facilitate all the configuration steps, guiding users through these steps, and performing all possible tasks in an automated way. As future work, we believe that it would make sense to develop a software tool with a Graphical User Interface (GUI) to support, for each of the building blocks, the execution of the several required configuration steps. For example, in an ANNODE solution, the user would navigate the software tool to issue the training of the required ANNs by providing a valid training dataset. The same options would be provided to the user for the Failure Detection block, in the selection of the comparison method and related threshold setting according to the sensor network overall purpose. Integrating forecast models results in this workflow along with the possibility of selecting which sensors to be used in the dependability analysis would also contribute towards a robust and flexible tool, fit for both research and operational goals.

Machine learning techniques

Given that the strategies based on machine learning techniques that implement the Prediction and the Failure Detection blocks are of the utmost importance for the success of the instantiated solutions, an open issue concerns the investigation of alternative machine learning techniques, or even refinements of the considered ANN-based technique (e.g., considering different neural network structures), which could lead to even better prediction models. For instance, other techniques, such as linear combinations of features, decision trees or nearest neighbor algorithms, could also be used. For each one it would be relevant to investigate their appropriateness to solve this problem, by measuring the achievable accuracy in the estimation of target sensor measurements based on the mentioned correlations.

Concerning the definition of the Failure Detection block, there exist alternatives to the statistical technique that we proposed to instantiate the comparison method, namely classification algorithms. Some options that may be explored in future work include support vector machines, principal component analysis, fuzzy logic, naive bayes classifier, clustering, random forest, among others. Again, a feasibility study should be considered not only to check if each technique solves the comparison problem but also to evaluate if it can also be used for, and how well it supports, the estimation of the quality coefficient by the Quality Evaluation block.

Generalization of the Failure Detection strategies

In chapters 5 and 6, we evaluated the instantiations of the proposed dependability oriented monitoring methodology using SATURN datasets and defining concrete strategies for failure detection. These strategies were defined for the considered use cases and hence for the specific number of four sensors. Reasoning about the distinction between failures and events was, in that way, partially constrained to this number of sensors. Given that in real systems the number of sensors might be much larger, it would be useful to generalize the reasoning to an arbitrary number. Our work already points the fundamental directions, but we believe that the problem can be made more complex, and more challenging, by bringing into consideration the degree of correlation between sensors.

Improvements in the Quality Evaluation

As mentioned in Section 7.1, the idea of assigning a data quality coefficient to each new measurement is one of the contributions of this work towards achieving a dependability-oriented monitoring approach. The defined and implemented strategy for the calculation of this coefficient takes in consideration the significance of the similarity between the current target sensor measurement and the corresponding predictions for the expected value, which are generated by the prediction models in the Prediction block. Even though this strategy already assumes the existence of correlations between measurements provided over time by all sensors in the network (the prediction models, depending on the strategy, make use of a representative history of the sensors' measurements), we may also explore other types of information when calculating the coefficient. For instance, it may be relevant to consider the quality of past measurements, that is, the values of previously calculated quality coefficients, exploring the fact that most failure modes do not lead to an abrupt change of quality. Exploring the time variability of the quality values, in particular for sensor maintenance or sensor comparison, may also be an interesting issue.

It might be also interesting to derive a global quality indicator for the entire monitoring system, besides providing a quality coefficient for each measurement. This global quantification of quality might be derived not only from all the individual quality coefficients, but also by evaluating the degree of correlation among data provided by the multiple sensors. In fact, a monitoring system whose sensors provide data with a relevant degree of correlation will facilitate the automated detection of failures and the provision of corrected and better quality data.

References

[1] Citypulse smart city dataset collection. http://iot.ee.surrey.ac.uk:8080/datasets.html, 2019. Accessed: 2018-12-08. 38

[2] Climate forecast system. https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/climate-forecast-system-version2-cfsv2, 2019. Accessed: 2018-12-08. 66

[3] Global forecast system. https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs, 2019. Accessed: 2018-12-08. 66

[4] Hudson river environmental conditions observing system. http://www.hrecos.org/, 2019. Accessed: 2018-12-08. 40

[5] Intel lab data. http://db.csail.mit.edu/labdata/labdata.html, 2019. Accessed: 2018-12-08. 39, 108

[6] Lifeunderyourfeet. http://www.lifeunderyourfeet.org/, 2019. Accessed: 2018-12-08. 39

[7] Namos: Networked aquatic microbial observing system. http://robotics.usc.edu/~namos/index.html, 2019. Accessed: 2018-12-08. 39

[8] National centers for environmental prediction. https://www.ncep.noaa.gov/, 2019. Accessed: 2018-12-08. 66

[9] National oceanic and atmospheric administration. https://www.noaa.gov/, 2019. Accessed: 2018-12-08. 66

[10] North american mesoscale forecast system. https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/north-american-mesoscale-forecast-system-nam, 2019. Accessed: 2018-12-08. 66

[11] Odds - outlier detection datasets. http://odds.cs.stonybrook.edu/, 2019. Accessed: 2018-12-08. 38

[12] Openml. https://www.openml.org/search?type=data, 2019. Accessed: 2018-12-08. 38

[13] Rapid refresh. https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/rapid-refresh-rap, 2019. Accessed: 2018-12-08. 66

[14] River and estuary observatory network. https://www.bire.org/river-and-estuary-observatory-network/, 2019. Accessed: 2018-12-08. 40

[15] Saturn-04 chlorophyll sensor fouling. http://www.stccmop.org/files/s4-chl08.pdf, 2019. Accessed: 2013-06-30. 50, 117

[16] Sensorscope: Sensor networks for environmental monitoring. http://sensorscope.epfl.ch/, 2019. Accessed: 2018-12-08. 39

[17] Smartsantander. http://www.smartsantander.eu/, 2019. Accessed: 2018-12-08. 39

[18] Uci machine learning repository: Data sets. https://archive.ics.uci.edu/ml/datasets.html, 2019. Accessed: 2018-12-08. 38

[19] University of oregon solar radiation monitoring laboratory. http://solardata.uoregon.edu, 2019. Accessed: 2018-12-08. 39

[20] Water quality monitoring. https://www.nps.gov/im/sfan/water-quality.htm, 2019. Accessed: 2018-12-08. 40

[21] Abid, A., Kachouri, A., Kaaniche, H., and Abid, M. Quality of service in wireless sensor networks through a failure-detector with voting mechanism. In Computer Applications Technology (ICCAT), 2013 International Conference on (Jan 2013), pp. 1–5. 33

[22] Ahmed, M., Huang, X., and Sharma, D. A novel misbehavior evaluation with dempster-shafer theory in wireless sensor networks. In Proceedings of the Thirteenth ACM International Symposium on Mobile Ad Hoc Networking and Computing (New York, NY, USA, 2012), MobiHoc '12, ACM, pp. 259–260. 31

[23] Akyildiz, I., Pompili, D., and Melodia, T. Underwater acoustic sensor networks: research challenges. Ad Hoc Networks 3, 3 (2005), 257–279. 36

[24] Alferes, J., Lynggaard-Jensen, A., Munk-Nielsen, T., Tik, S., Vezzaro, L., Sharma, A., Mikkelsen, P., and Vanrolleghem, P. Validating data

quality during wet weather monitoring of wastewater treatment plant influents. Proceedings of the Water Environment Federation 2013, 12 (2013), 4507–4520. 31, 51

[25] Andrade, A. T. C., Montez, C., Moraes, R., Pinto, A. R., Vasques, F., and da Silva, G. L. Outlier detection using k-means clustering and lightweight methods for wireless sensor networks. In IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society (Oct 2016), pp. 4683–4688. 90

[26] Anghel, L., Alexandrescu, D., and Nicolaidis, M. Evaluation of a soft error tolerance technique based on time and/or space redundancy. In Proceedings 13th Symposium on Integrated Circuits and Systems Design (Cat. No. PR00843) (2000), IEEE, pp. 237–242. 11

[27] Archer, C., Baptista, A., and Leen, T. Fault detection for salinity sensors in the columbia estuary. Tech. rep., 2002. 31, 42, 51

[28] Avizienis, A., Laprie, J.-C., Randell, B., and Landwehr, C. Basic concepts and taxonomy of dependable and secure computing. IEEE Trans. Dependable Secur. Comput. 1, 1 (Jan. 2004), 11–33. 12

[29] Ayadi, A., Ghorbel, O., Bensaleh, M. S., Obeid, A., and Abid, M. Performance of outlier detection techniques based classification in wireless sensor networks. In 2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC) (June 2017), pp. 687–692. 90

[30] Ayadi, A., Ghorbel, O., Obeid, A. M., and Abid, M. Outlier detection approaches for wireless sensor networks. Computer Networks 129, P1 (Dec. 2017), 319–333. 90

[31] Ayday, E., Delgosha, F., and Fekri, F. Data authenticity and availability in multihop wireless sensor networks. ACM Trans. Sen. Netw. 8, 2 (Mar. 2012), 10:1–10:26. 12

[32] Bahrepour, M., Meratnia, N., and Havinga, P. J. M. Sensor fusion-based event detection in wireless sensor networks. In 2009 6th Annual International Mobile and Ubiquitous Systems: Networking Services, MobiQuitous (July 2009), pp. 1–8. 89

[33] Bahrepour, M., Meratnia, N., Poel, M., Taghikhaki, Z., and Havinga, P. Distributed event detection in wireless sensor networks for disaster manage-

ment. In Intelligent Networking and Collaborative Systems (INCOS), 2010 2nd International Conference on (Nov 2010), pp. 507–512. 31, 89

[34] Balzano, L., and Nowak, R. Blind calibration of sensor networks. In Proceedings of the 6th international conference on Information processing in sensor networks (2007), ACM, pp. 79–88. 116

[35] Baptista, A. Environmental observation and forecasting systems. In Encyclopedia of Physical Science and Technology (Third Edition), R. A. Meyers, Ed., third edition ed. Academic Press, New York, 2003, pp. 565–581. 40, 41, 42

[36] Barron, J., Moustapha, A., and Selmic, R. Real-time implementation of fault detection in wireless sensor networks using neural networks. In Information Technology: New Generations, 2008. ITNG 2008. Fifth International Conference on (April 2008), pp. 378–383. 31

[37] Barwicz, A., Massicotte, D., Savaria, Y., Santerre, M.-A., and Morawski, R. An integrated structure for kalman-filter-based measurand reconstruction. Instrumentation and Measurement, IEEE Transactions on 43, 3 (Jun 1994), 403–410. 21

[38] Bettencourt, L., Hagberg, A., and Larkey, L. Separating the wheat from the chaff: Practical anomaly detection schemes in ecological applications of distributed sensor networks. In Distributed Computing in Sensor Systems, J. Aspnes, C. Scheideler, A. Arora, and S. Madden, Eds., vol. 4549 of Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2007, pp. 223–239. 32, 51, 55, 58

[39] Boano, C. A., Tsiftes, N., Voigt, T., Brown, J., and Roedig, U. The impact of temperature on outdoor industrial sensornet applications. IEEE Transactions on Industrial Informatics 6, 3 (Aug 2010), 451–459. xi, 3

[40] Boudjemaa, R., and Forbes, A. Parameter Estimation Methods for Data Fusion. NPL report CMSC. National Physical Laboratory. Great Britain, Centre for Mathematics and Scientific Computing, 2004. 24, 25

[41] Brade, T., Kaiser, J., and Zug, S. Expressing validity estimates in smart sensor applications. In Architecture of Computing Systems (ARCS), Proceedings of 2013 26th International Conference on (Feb 2013), pp. 1–8. 9, 12, 14, 19

[42] Branch, J., Giannella, C., Szymanski, B., Wolff, R., and Kargupta, H. In-network outlier detection in wireless sensor networks. Knowledge and Information Systems 34, 1 (2013), 23–54. 33

[43] Brooks, R., and Iyengar, S. Multi-sensor Fusion: Fundamentals and Applications with Software. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1998. 26

[44] Bychkovskiy, V., Megerian, S., Estrin, D., and Potkonjak, M. A collaborative approach to in-place sensor calibration. In Information Processing in Sensor Networks (2003), Springer, pp. 301–316. 116

[45] Castillo-Effer, M., Quintela, D., Moreno, W., Jordan, R., and Westhoff, W. Wireless sensor networks for flash-flood alerting. In Devices, Circuits and Systems, 2004. Proceedings of the Fifth IEEE International Caracas Conference on (Nov 2004), vol. 1, pp. 142–146. 32

[46] Chan, L.-w. Levenberg-marquardt learning and regularization. In in Progress in Neural Information Processing (1996), Citeseer. 62, 95

[47] Chandola, V., Banerjee, A., and Kumar, V. Anomaly detection: A survey. ACM Comput. Surv. 41, 3 (July 2009), 15:1–15:58. 28, 89

[48] Chatzigiannakis, V., Papavassiliou, S., Grammatikou, M., and Maglaris, B. Hierarchical anomaly detection in distributed large-scale sensor networks. In Computers and Communications, 2006. ISCC '06. Proceedings. 11th IEEE Symposium on (June 2006), pp. 761–767. 33

[49] Chelli, K. Security issues in wireless sensor networks: Attacks and countermeasures. In Proceedings of the World Congress on Engineering (2015), vol. 1. 23

[50] Chen, C., Liu, H., and Beardsley, R. An unstructured grid, finite-volume, three-dimensional, primitive equations ocean model: Application to coastal ocean and estuaries. Journal of Atmospheric and Oceanic Technology 20, 1 (2003), 159–186. 35

[51] Choi, S., Yuh, J., and Takashige, G. Development of the Omni Directional Intelligent Navigator. IEEE Robotics & Automation Magazine 2, 1 (1995). 27

[52] Chouikhi, S., El Korbi, I., Ghamri-Doudane, Y., and Saidane, L. A. A survey on fault tolerance in small and large scale wireless sensor networks. Computer Communications 69 (2015), 22–37. xii, 4

[53] Codiga, D., Rice, J., and Baxley, P. Networked acoustic modems for real-time data delivery from distributed subsurface instruments in the coastal ocean:

Initial system development and performance. Journal of Atmospheric and Oceanic Technology 21, 2 (2004), 331–346. 36

[54] Collotta, M., Pau, G., Salerno, V., and Scata, G. A fuzzy based algorithm to manage power consumption in industrial wireless sensor networks. In Industrial Informatics (INDIN), 2011 9th IEEE International Conference on (July 2011), pp. 151–156. 32

[55] Council, N. R., et al. Expanding the vision of sensor materials. National Academies Press, 1995. 15

[56] Crespi, A., and Ijspeert, A. Online optimization of swimming and crawling in an amphibious snake robot. IEEE Transactions on Robotics 24, 1 (2008), 75–87. 27

[57] Cristian, F. Understanding fault-tolerant distributed systems. Commun. ACM 34, 2 (Feb. 1991), 56–78. 10

[58] Cui, J.-H., Kong, J., Gerla, M., and Zhou, S. The challenges of building mobile underwater wireless networks for aquatic applications. Network, IEEE 20, 3 (May 2006), 12–18. 35

[59] David, L., Rodrigues, M., Fortunato, A., Oliveira, A., Mota, T., Costa, J., Rogeiro, J., Jesus, G., Gomes, J., Menaia, J., et al. Demonstration system for early warning of faecal contamination in recreational waters in lisbon. Climate Change, Water Supply and Sanitation: Risk Assessment, Management, Mitigation and Reduction, IWA Publishing, Hulsmann A. et al.(eds) (2015). 35

[60] de Bruijn, B., Nguyen, T. A., Bucur, D., and Tei, K. Benchmark datasets for fault detection and classification in sensor data. In SENSORNETS (2016), pp. 185–195. 76

[61] de Jesus, G., Santos, M., and Palha-Fernandes, J. Sage-b: a dynamic dam-break flood emergency management system. WIT Transactions on Ecology and the Environment 133 (2010), 119–127. 1

[62] De Silva, C. Control sensors and actuators. Prentice Hall, 1989. 17

[63] Dereszynski, E. W., and Dietterich, T. G. Spatiotemporal models for data-anomaly detection in dynamic environmental monitoring campaigns. ACM Transactions on Sensor Networks 8, 1 (Aug. 2011), 3:1–3:36. xi, 3, 74

[64] Dietrich, A., Zug, S., and Kaiser, J. Detecting external measurement disturbances based on statistical analysis for smart sensors. In Industrial Electronics (ISIE), 2010 IEEE International Symposium on (July 2010), pp. 2067–2072. 9

[65] Durrant-Whyte, H. Sensor models and multisensor integration. Int. J. Rob. Res. 7, 6 (Dec. 1988), 97–113. 28

[66] Eickstedt, D., Benjamin, M., Schmidt, H., and Leonard, J. Adaptive control of heterogeneous marine sensor platforms in an autonomous sensor network. In Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on (Oct 2006), pp. 5514–5521. 37

[67] Etter, P. Underwater Acoustic Modeling: Principles, techniques and applications, Second Edition. Taylor & Francis, 1995. 35

[68] Feng, J., Megerian, S., and Potkonjak, M. Model-based calibration for sensor networks. Sensors 2 (2003), 737–742. 116

[69] Fortunato, A. B., Oliveira, A., Rogeiro, J., Tavares da Costa, R., Gomes, J. L., Li, K., de Jesus, G., Freire, P., Rilo, A., Mendes, A., et al. Operational forecast framework applied to extreme sea levels at regional and local scales. Journal of Operational Oceanography 10, 1 (2017), 1–15. 1, 35

[70] Fraden, J. Handbook of modern sensors: physics, designs, and applications. Springer Science & Business Media, 2004. 15

[71] Frolik, J., Abdelrahman, M., and Kandasamy, P. A confidence-based approach to the self-validation, fusion and reconstruction of quasi-redundant sensor data. IEEE Transactions on Instrumentation and Measurement 50, 6 (2001), 1761–1769. 12, 13, 14

[72] Funnemark, E., and Odgaard, E. Svendsen. vn, and amdal, t.: Consequence analysis of dam breaks. Dam safety, Balkema, edited by Berga, L., Rotterdam (1998), 329–336. 1

[73] Gaillard, F., Autret, E., Thierry, V., Galaup, P., Coatanoan, C., and Loubrieu, T. Quality control of large argo datasets. Journal of Atmospheric and Oceanic Technology 26, 2 (2009), 337–351. 37

[74] Ganesan, D., Estrin, D., and Heidemann, J. Dimensions: why do we need a new data handling architecture for sensor networks. ACM SIGCOMM Computer Communication Review 33, 1 (2003), 143–148. 22

[75] Gao, J., Xu, Y., and Li, X. Online distributed fault detection of sensor measurements. Tsinghua Science and Technology 12, S1 (July 2007), 192–196. 33

[76] Ghorbel, O., Ayedi, W., Snoussi, H., and Abid, M. Fast and efficient outlier detection method in wireless sensor networks. IEEE Sensors Journal 15, 6 (June 2015), 3403–3411. 90

[77] Golle, P., Greene, D., and Staddon, J. Detecting and correcting malicious data in vanets. In Proceedings of the 1st ACM International Workshop on Vehicular Ad Hoc Networks (New York, NY, USA, 2004), VANET '04, ACM, pp. 29–37. 14

[78] Gomes, J., Jesus, G., Rodrigues, M., Rogeiro, J., Azevedo, A., and Oliveira, A. Managing a coastal sensors network in a nowcast-forecast information system. In Broadband and Wireless Computing, Communication and Applications (BWCCA), 2013 Eighth International Conference on (Oct 2013), pp. 518–523. 26, 47

[79] Gomes, J. L., Jesus, G., Rogeiro, J., Oliveira, A., da Costa, R. T., and Fortunato, A. B. An innovative web platform for flood risk management. In International Conference on Innovative Network Systems and Applications (2015), Springer, pp. 217–231. xi, 2

[80] Grime, S., and Durrant-Whyte, H. Data fusion in decentralized sensor networks. Control Engineering Practice 2, 5 (1994), 849–863. 25

[81] Gubian, M., Marconato, A., Boni, A., and Petri, D. A study on uncertainty-complexity tradeoffs for dynamic nonlinear sensor compensation. Instrumentation and Measurement, IEEE Transactions on 58, 1 (Jan 2009), 26–32. 21

[82] Gupta, M., Gao, J., Aggarwal, C. C., and Han, J. Outlier detection for temporal data: A survey. IEEE Transactions on Knowledge and Data Engineering 26, 9 (Sept 2014), 2250–2267. 90

[83] Hadi, A. S., Imon, A. H. M. R., and Werner, M. Detection of outliers. Wiley Interdisciplinary Reviews: Computational Statistics 1, 1 (2009), 57–70. 90

[84] Haidvogel, D., Arango, H., Budgell, W., Cornuelle, B., Curchitser, E., Di Lorenzo, E., Fennel, K., Geyer, W., Hermann, A., Lanerolle, L., Levin, J., McWilliams, J., Miller, A., Moore, A., Powell, T., Shchepetkin, A., Sherwood, C., Signell, R., Warner, J., and Wilkin, J. Ocean

forecasting in terrain-following coordinates: Formulation and skill assessment of the regional ocean modeling system. Journal of Computational Physics 227, 7 (2008), 3595–3624. 35

[85] Hall, D., and McMullen, S. Mathematical Techniques in Multisensor Data Fusion (Artech House Information Warfare Library). Artech House, Inc., Norwood, MA, USA, 2004. 30

[86] Hartl, G., and Li, B. infer: A bayesian inference approach towards energy efficient data collection in dense sensor networks. In Distributed Computing Systems, 2005. ICDCS 2005. Proceedings. 25th IEEE International Conference on (June 2005), pp. 371–380. 30

[87] Herbert, D., Sundaram, V., Lu, Y.-H., Bagchi, S., and Li, Z. Adaptive correctness monitoring for wireless sensor networks using hierarchical distributed runtime invariant checking. ACM Transactions on Autonomous and Adaptive Systems (TAAS) 2, 3 (2007), 8. 74

[88] Hope, M. E., Westerink, J. J., Kennedy, A. B., Kerr, P., Dietrich, J. C., Dawson, C., Bender, C. J., Smith, J., Jensen, R. E., Zijlema, M., et al. Hindcast and validation of hurricane ike (2008) waves, forerunner, and storm surge. Journal of Geophysical Research: Oceans 118, 9 (2013), 4424–4460. 67

[89] Huang, G.-B. Learning capability and storage capacity of two-hidden-layer feedforward networks. IEEE Transactions on Neural Networks 14, 2 (2003), 274–281. 62

[90] Huang, G.-B., Zhu, Q.-Y., Siew, C.-K., et al. Extreme learning machine: a new learning scheme of feedforward neural networks. Neural networks 2 (2004), 985–990. 61

[91] Ibargiengoytia, P., Sucar, L., and Vadera, S. Real time intelligent sensor validation. IEEE Transactions on Power Systems 16, 4 (2001), 770–775. 11, 14

[92] Isermann, R. Model-based fault-detection and diagnosis – status and applications. Annual Reviews in Control 29, 1 (2005), 71–85. 27

[93] Janakiram, D., Reddy, V., and Kumar, A. Outlier detection in wireless sensor networks using bayesian belief networks. In Communication System Software and Middleware, 2006. Comsware 2006. First International Conference on (2006), pp. 1–6. 31

[94] Jesus, G., Oliveira, A., Azevedo, A., and Casimiro, A. Improving sensor-fusion with environmental models. In 2015 IEEE SENSORS (2015), IEEE, pp. 1–4. 24

[95] Kamal, S., Ramadan, R. A., and Fawzy, E.-R. Smart outlier detection of wireless sensor network. Facta Universitatis, Series: Electronics and Energetics 19, 3 (2016), 383–393. 90

[96] Karsoliya, S. Approximating number of hidden layer neurons in multiple hidden layer bpnn architecture. International Journal of Engineering Trends and Technology 3, 6 (2012), 714–717. 62

[97] Kermani, B. G., Schiffman, S. S., and Nagle, H. T. Performance of the levenberg–marquardt neural network training method in electronic nose applications. Sensors and Actuators B: Chemical 110, 1 (2005), 13–22. 62

[98] Kerr, P., Martyr, R., Donahue, A., Hope, M., Westerink, J., Luettich, R., Kennedy, A., Dietrich, J., Dawson, C., and Westerink, H. Us ioos coastal and ocean modeling testbed: Evaluation of tide, wave, and hurricane surge response sensitivities to mesh resolution and friction in the gulf of mexico. Journal of Geophysical Research: Oceans 118, 9 (2013), 4633–4661. 67

[99] Khaleghi, B., Khamis, A., Karray, F., and Razavi, S. Multisensor data fusion: A review of the state-of-the-art. Information Fusion 14, 1 (2013), 28–44. 30

[100] Khan, S., Daachi, B., and Djouani, K. Application of fuzzy inference systems to detection of faults in wireless sensor networks. Neurocomput. 94 (Oct. 2012), 111–120. 32

[101] Kilfoyle, D., and Baggeroer, A. The state of the art in underwater acoustic telemetry. Oceanic Engineering, IEEE Journal of 25, 1 (Jan 2000), 4–27. 35

[102] Kishi, M., Kashiwai, M., Ware, D., Megrey, B., Eslinger, D., Werner, F., Noguchi-Aita, M., Azumaya, T., Fujii, M., Hashimoto, S., Huang, D., Iizumi, H., Ishida, Y., Kang, S., Kantakov, G., Kim, H., Komatsu, K., Navrotsky, V., Smith, S., Tadokoro, K., Tsuda, A., Yamamura, O., Yamanaka, Y., Yokouchi, K., Yoshie, N., Zhang, J., Zuenko, Y., and Zvalinsky, V. Nemuro - a lower trophic level model for the north pacific marine ecosystem. Ecological Modelling 202, 1-2 (2007), 12–25. 35

[103] Klein, L. Sensor and Data Fusion Concepts and Applications, 2nd ed. Society of Photo-Optical Instrumentation Engineers (SPIE), Bellingham, WA, USA, 1999. 30

[104] Klein, L. Sensor and Data Fusion: A Tool for Information Assessment and Decision Making. Press Monographs. Society of Photo Optical, 2004. 27, 32, 33

[105] Klein, L., Mihaylova, L., and El Faouzi, N.-E. Sensor and data fusion:taxonomy, challenges and applications. In Handbook on Soft Computing for Video Surveillance, S. K. Pal, A. Petrosino, and L. Maddalena, Eds., 1st ed. Chapman & Hall/CRC, 2012, ch. 6. 31

[106] Konorski, J., and Orlikowski, R. Data-centric dempster-shafer theory-based selfishness thwarting via trust evaluation in manets and wsns. In New Technologies, Mobility and Security (NTMS), 2009 3rd International Conference on (Dec 2009), pp. 1–5. 31

[107] Kopetz, H. Real-Time Systems: Design Principles for Distributed Embedded Applications. Real-Time Systems Series. Springer US, 2011. 22

[108] Koren, I., and Krishna, C. M. Fault-tolerant systems. Elsevier, 2010. 11

[109] Koushanfar, F., Potkonjak, M., and Sangiovanni-Vincentelli, A. Online fault detection of sensor measurements. In Sensors, 2003. Proceedings of IEEE (Oct 2003), vol. 2, pp. 974–979 Vol.2. 24

[110] Krishnamachari, L., Estrin, D., and Wicker, S. The impact of data aggregation in wireless sensor networks. In Proceedings 22nd International Conference on Distributed Computing Systems Workshops (2002). 22

[111] Kumar, D., Rajasegarar, S., and Palaniswami, M. Automatic sensor drift detection and correction using spatial kriging and kalman filtering. In Distributed Computing in Sensor Systems (DCOSS), 2013 IEEE International Conference on (2013), IEEE, pp. 183–190. 116

[112] Kumar, D., Rajasegarar, S., and Palaniswami, M. Geospatial estimation-based auto drift correction in wireless sensor networks. ACM Transactions on Sensor Networks (TOSN) 11, 3 (2015), 50. 116

[113] Li, F., and Wu, J. A probabilistic voting-based filtering scheme in wireless sensor networks. In Proceedings of the 2006 International Conference on Wireless Communications and Mobile Computing (New York, NY, USA, 2006), IWCMC '06, ACM, pp. 27–32. 33

[114] Luettich Jr, R., Westerink, J., and Scheffner, N. W. Adcirc: An advanced three-dimensional circulation model for shelves, coasts, and estuaries. report

1. theory and methodology of adcirc-2ddi and adcirc-3dl. Tech. rep., COASTAL ENGINEERING RESEARCH CENTER VICKSBURG MS, 1992. 35

[115] Luo, H., Tao, H., Ma, H., and Das, S. Data fusion with desired reliability in wireless sensor networks. Parallel and Distributed Systems, IEEE Transactions on 22, 3 (March 2011), 501–513. 12, 88

[116] Madden, S., Franklin, M., Hellerstein, J., and Hong, W. Tag: A tiny aggregation service for ad-hoc sensor networks. SIGOPS Oper. Syst. Rev. 36, SI (Dec. 2002), 131–146. 22

[117] Mainwaring, A., Culler, D., Polastre, J., Szewczyk, R., and Anderson, J. Wireless sensor networks for habitat monitoring. In Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications (2002), Acm, pp. 88–97. 39

[118] Makhija, D., Kumaraswamy, P., and Roy, R. Challenges and design of mac protocol for underwater acoustic sensor networks. In Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks, 2006 4th International Symposium on (April 2006), pp. 1–6. 35

[119] Manjunatha, P., Verma, A., and Srividya, A. Multi-sensor data fusion in cluster based wireless sensor networks using fuzzy logic method. In Industrial and Information Systems, 2008. ICIIS 2008. IEEE Region 10 and the Third international Conference on (Dec 2008), pp. 1–6. 32

[120] Marzullo, K. Tolerating failures of continuous-valued sensors. ACM Trans. Comput. Syst. 8, 4 (Nov. 1990), 284–304. 24, 26

[121] Mendonca, R., Santana, P., Marques, F., Lourenco, A., Silva, J., and Barata, J. Kelpie: A ros-based multi-robot simulator for water surface and aerial vehicles. In Systems, Man, and Cybernetics (SMC), 2013 IEEE International Conference on (Oct 2013), pp. 3645–3650. 27

[122] Mitchell, H. Multi-sensor data fusion: An introduction. 2007. 17

[123] Montella, C. The kalman filter and related algorithms: A literature review. Tech. rep., Tech. rep., Lehigh University, 2011. 55

[124] Moustapha, A., and Selmic, R. Wireless sensor network modeling using modified recurrent neural networks: Application to fault detection. Instrumentation and Measurement, IEEE Transactions on 57, 5 (May 2008), 981–988. 31, 89

[125] Nakamura, E., Loureiro, A., and Frery, A. Information fusion for wireless sensor networks: Methods, models, and classifications. ACM Comput. Surv. 39, 3 (Sept. 2007). 26, 30

[126] Nguyen, D., and Widrow, B. Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights. In 1990 IJCNN International Joint Conference on Neural Networks (1990), IEEE, pp. 21–26. 62

[127] Nimier, V. Supervised multisensor tracking algorithm. In Signal Processing Conference (EUSIPCO 1998), 9th European (Sept 1998), pp. 1–4. 14

[128] Obst, O. Poster abstract: Distributed fault detection using a recurrent neural network. In Proceedings of the 2009 International Conference on Information Processing in Sensor Networks (Washington, DC, USA, 2009), IPSN '09, IEEE Computer Society, pp. 373–374. 31

[129] Paola, A. D., Gaglio, S., Re, G. L., Milazzo, F., and Ortolani, M. Adaptive distributed outlier detection for wsns. IEEE Transactions on Cybernetics 45, 5 (May 2015), 902–913. 90

[130] Park, K., Jung, H.-S., Kim, H.-S., and Ahn, S.-M. Three-dimensional hydrodynamic-eutrophication model (hem-3d): application to kwang-yang bay, korea. Marine Environmental Research 60, 2 (2005), 171–193. 35

[131] Parker, D. J., and Priest, S. J. The fallibility of flood warning chains: can europe's flood warnings be effective? Water resources management 26, 10 (2012), 2927–2950. 2

[132] Patra, J., Bornand, C., and Chakraborty, G. Hermite neural network-based intelligent sensors for harsh environments. In Neural Networks, 2009. IJCNN 2009. International Joint Conference on (June 2009), pp. 2439–2444. 14

[133] Patra, J., Chakraborty, G., and Meher, P. Neural-network-based robust linearization and compensation technique for sensors under nonlinear environmental influences. IEEE Transactions on Circuits and Systems I: Regular Papers 55, 5 (2008), 1316–1327. 16

[134] Patra, J., Meher, P., and Chakraborty, G. Development of laguerre neural-network-based intelligent sensors for wireless sensor networks. Instrumentation and Measurement, IEEE Transactions on 60, 3 (March 2011), 725–734. 21, 116

[135] Peng, M., Xie, L., and Pietrafesa, L. J. A numerical study of storm surge and inundation in the croatan–albemarle–pamlico estuary system. Estuarine, Coastal and Shelf Science 59, 1 (2004), 121–137. 67

[136] Peng, N., Zhang, W., Ling, H., Zhang, Y., and Zheng, L. Fault-tolerant anomaly detection method in wireless sensor networks. Information 9, 9 (2018), 236. 78

[137] Pradhan, A. R., Laefer, D. F., and Rasdorf, W. J. Infrastructure management information system framework requirements for disasters. Journal of computing in civil engineering 21, 2 (2007), 90–101. 1

[138] Proakis, J., Sozer, E., Rice, J., and Stojanovic, M. Shallow water acoustic networks. Communications Magazine, IEEE 39, 11 (Nov 2001), 114–119. 35

[139] Pugh, D. T. Tides, surges, and mean sea-level. Chichester ; New York : J. Wiley, 1987. "A handbook for engineers and scientists"–Cover. 42

[140] Raghunath, K. K., and Rengarajan, N. Investigation of faults, errors and failures in wireless sensor network: A systematical survey. International Journal of Advanced Computer Research 3, 3 (2013), 151. 22

[141] Rajasegarar, S., Leckie, C., Bezdek, J. C., and Palaniswami, M. Centered hyperspherical and hyperellipsoidal one-class support vector machines for anomaly detection in sensor networks. IEEE Transactions on Information Forensics and Security 5, 3 (Sept 2010), 518–533. 110

[142] Rassam, M. A., Maarof, M. A., and Zainal, A. Adaptive and online data anomaly detection for wireless sensor systems. Knowledge-Based Systems 60 (2014), 44–57. 91, 109, 110, 111, 112

[143] Rathore, P., Kumar, D., Rajasegarar, S., and Palaniswami, M. Bayesian maximum entropy and interacting multiple model based automatic sensor drift detection and correction in an iot environment. In 2018 IEEE 4th World Forum on Internet of Things (WF-IoT) (2018), IEEE, pp. 598–603. 116

[144] Ripka, P. Master book on sensors: modular courses on modern sensors; Leonardo da Vinci project CZ/PP-134026. Czech Techn. Univ., 2003. 16

[145] Ripka, P., and Tipek, A. Modern sensors handbook. John Wiley & Sons, 2013. 15

[146] Rivera, J., Carrillo, M., Chacón, M., Herrera, G., and Bojorquez, G. Self-calibration and optimal response in intelligent sensors design based on artificial neural networks. Sensors 7, 8 (2007), 1509. 21, 116

[147] Rodger, J. Toward reducing failure risk in an integrated vehicle health maintenance system: A fuzzy multi-sensor data fusion kalman filter approach for {IVHMS}. Expert Systems with Applications 39, 10 (2012), 9821–9836. 12

[148] Rodrigues, M., Oliveira, A., Guerreiro, M., Fortunato, A., Menaia, J., David, L., and Cravo, A. Modeling fecal contamination in the aljezur coastal stream (portugal). Ocean Dynamics 61, 6 (2011), 841–856. 35

[149] Rodrigues, M., Oliveira, A., Queiroga, H., Fortunato, A., and Zhang, Y. Three-dimensional modeling of the lower trophic levels in the ria de aveiro (portugal). Ecological Modelling 220, 9-10 (2009), 1274–1290. 35

[150] Sattele, M., Brundl, M., and Straub, D. Reliability and effectiveness of early warning systems for natural hazards: Concept and application to debris flow warning. Reliability Engineering & System Safety 142 (2015), 192–202. 10

[151] Schubert, E., Zimek, A., and Kriegel, H.-P. Local outlier detection reconsidered: A generalized view on locality with applications to spatial, video, and network outlier detection. Data Mining and Knowledge Discovery 28, 1 (Jan. 2014), 190–237. 90

[152] Sen, J. Routing security issues in wireless sensor networks: attacks and defenses. Sustainable Wireless Sensor Networks (2010), 279–309. 22

[153] Sentz, K., Ferson, S., and Laboratories, S. N. Combination of Evidence in Dempster-Shafer Theory. Sand (Sandia National Laboratories). Sandia National Laboratories, 2002. 31

[154] Shahid, N., Naqvi, I. H., and Qaisar, S. B. Characteristics and classification of outlier detection techniques for wireless sensor networks in harsh environments: A survey. Artif. Intell. Rev. 43, 2 (Feb. 2015), 193–228. 91

[155] Sharma, A., Golubchik, L., and Govindan, R. Sensor faults: Detection methods and prevalence in real-world datasets. ACM Trans. Sen. Netw. 6, 3 (June 2010), 23:1–23:39. 4, 13

[156] Shell, J., Coupland, S., and Goodyer, E. Fuzzy data fusion for fault detection in wireless sensor networks. In Computational Intelligence (UKCI), 2010 UK Workshop on (Sept 2010), pp. 1–6. 32

[157] Smith, P. J., Hughes, D., Beven, K. J., Cross, P., Tych, W., Coulson, G., and Blair, G. Towards the provision of site specific flood warnings using wireless sensor networks. Meteorological Applications 16, 1 (2009), 57–64. xii, 3

[158] Su, I.-J., Tsai, C.-C., and Sung, W.-T. Area temperature system monitoring and computing based on adaptive fuzzy logic in wireless sensor networks. Appl. Soft Comput. 12, 5 (May 2012), 1532–1541. 32

[159] Su, X., and Tsai, C.-L. Outlier detection. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 1, 3 (2011), 261–268. 90

[160] Sunkpho, J., and Ootamakorn, C. Real-time flood monitoring and warning system. Songklanakarin Journal of Science & Technology 33, 2 (2011). xi, 2

[161] Szewczyk, R., Mainwaring, A., Polastre, J., Anderson, J., and Culler, D. An analysis of a large scale habitat monitoring application. In Proceedings of the 2nd international conference on Embedded networked sensor systems (2004), ACM, pp. 214–226. 4

[162] Takruri, M., Aboura, K., and Challa, S. Distributed recursive algorithm for auto calibration in drift aware wireless sensor networks. In Innovations and advanced techniques in systems, computing sciences and software engineering. Springer, 2008, pp. 21–25. 116

[163] Takruri, M., and Challa, S. Drift aware wireless sensor networks. In Information Fusion, 2007 10th International Conference on (2007), IEEE, pp. 1–7. 116

[164] Takruri, M., and Challa, S. Data fusion approach for error correction in wireless sensor networks. In Wireless Sensor Networks: Application-Centric Design. InTech, 2010. 116

[165] Takruri, M., Challa, S., and Chakravorty, R. Auto calibration in drift aware wireless sensor networks using the interacting multiple model algorithm. In Communications, Computers and Applications, 2008. MIC-CCA 2008. Mosharaka International Conference on (2008), IEEE, pp. 98–103. 116

[166] Takruri, M., Challa, S., and Chakravorty, R. Recursive bayesian approaches for auto calibration in drift aware wireless sensor networks. Journal of Networks (2010). 116

[167] Takruri, M., Challa, S., and Yunis, R. Data fusion techniques for auto calibration in wireless sensor networks. In Information Fusion, 2009. FUSIon'09. 12th International Conference on (2009), IEEE, pp. 132–139. 116

[168] Takruri, M., Rajasegarar, S., Challa, S., Leckie, C., and Palaniswami, M. Online drift correction in wireless sensor networks using spatio-temporal modeling. In Information Fusion, 2008 11th International Conference on (2008), IEEE, pp. 1–8. 116

[169] Tan, R., Xing, G., Liu, X., Yao, J., and Yuan, Z. Adaptive calibration for fusion-based cyber-physical systems. ACM Transactions on Embedded Computing Systems (TECS) 11, 4 (2012), 80. 116

[170] Tang, L., Yu, X., Kim, S., Gu, Q., Han, J., Leung, A., and La Porta, T. Trustworthiness analysis of sensor data in cyber-physical systems. Journal of Computer and System Sciences 79, 3 (2013), 383–401. 12

[171] Tolle, G., Polastre, J., Szewczyk, R., Culler, D., Turner, N., Tu, K., Burgess, S., Dawson, T., Buonadonna, P., Gay, D., et al. A macroscope in the redwoods. In Proceedings of the 3rd international conference on Embedded networked sensor systems (2005), ACM, pp. 51–63. 4

[172] Tumanski, S. Sensors and Actuators - Control System Instrumentation (de Silva, C.W.; 2007), vol. 10. 2007. 17

[173] Veeramony, J., Orzech, M. D., Edwards, K. L., Gilligan, M., Choi, J., Terrill, E., and De Paolo, T. Navy nearshore ocean prediction systems. Oceanography 27, 3 (2014), 80–91. 67

[174] Veríssimo, P., and Rodrigues, L. Distributed systems for system architects. 2001. 11, 24

[175] Wang, Y., Yang, A., Li, Z., Chen, X., Wang, P., and Yang, H. Blind drift calibration of sensor networks using sparse bayesian learning. IEEE Sensors Journal 16, 16 (2016), 6249–6260. 116

[176] Warriach, E. U., Aiello, M., and Tei, K. A machine learning approach for identifying and classifying faults in wireless sensor network. In Computational Science and Engineering (CSE), 2012 IEEE 15th International Conference on (2012), IEEE, pp. 618–625. 37, 116

[177] Webster, J., and Eren, H. Measurement, Instrumentation, and Sensors Handbook, Second E 2014. 16, 17

[178] Weisberg, R. H., and Zheng, L. Hurricane storm surge simulations comparing three-dimensional with two-dimensional formulations based on an ivan-like storm over the tampa bay, florida region. Journal of Geophysical Research: Oceans 113, C12 (2008). 67

[179] Whitehouse, K., and Culler, D. Calibration as parameter estimation in sensor networks. In Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications (New York, NY, USA, 2002), WSNA '02, ACM, pp. 59–67. 21, 116

[180] Worden, K., Manson, G., and Fieller, N. Damage detection using outlier analysis. Journal of Sound and Vibration 229, 3 (2000), 647–667. 27

[181] Xie, L., Liu, H., and Peng, M. The effect of wave–current interactions on the storm surge and inundation in charleston harbor during hurricane hugo 1989. Ocean modelling 20, 3 (2008), 252–269. 67

[182] Xie, L., Pietrafesa, L. J., and Peng, M. Incorporation of a mass-conserving inundation scheme into a three dimensional storm surge model. Journal of Coastal Research (2004), 1209–1223. 67

[183] Xie, L., Pietrafesa, L. J., and Wu, K. Interannual and decadal variability of landfalling tropical cyclones in the southeast coastal states of the united states. Advances in Atmospheric Sciences 19, 4 (2002), 677–686. 67

[184] Xie, Y.-x., Chen, X.-g., and Zhao, J. Data fault detection for wireless sensor networks using multi-scale pca method. In Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), 2011 2nd International Conference on (2011), IEEE, pp. 7035–7038. 116

[185] Xu, G., Shen, W., and Wang, X. Applications of wireless sensor networks in marine environment monitoring: a survey. Sensors 14, 9 (September 2014), 16932–16954. 37

[186] Yang, Z., Meratnia, N., and Havinga, P. An online outlier detection technique for wireless sensor networks using unsupervised quarter-sphere support vector machine. In 2008 International Conference on Intelligent Sensors, Sensor Networks and Information Processing (Dec 2008), pp. 151–156. 110

[187] Zappi, P., Stiefmeier, T., Farella, E., Roggen, D., Benini, L., and Troster, G. Activity recognition from on-body sensors by classifier fusion: sensor scalability and robustness. In Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on (Dec 2007), pp. 281–286. 33

[188] Zhang, D., Zhao, C., Liang, Y., and Liu, Z. A new medium access control protocol based on perceived data reliability and spatial correlation in wireless sensor network. Computers & Electrical Engineering 38, 3 (2012), 694–702. 12

[189] Zhang, Y., and Baptista, A. Selfe: A semi-implicit eulerian–lagrangian finite-element model for cross-scale ocean circulation. Ocean Modelling 21, 3–4 (2008), 71–96. 35

[190] Zhang, Y., and Baptista, A. M. Benchmarking a new open-source 3d circulation model (elcirc). In Developments in Water Science, vol. 55. Elsevier, 2004, pp. 1791–1800. 67

[191] Zhang, Y., and Baptista, A. M. Selfe: a semi-implicit eulerian–lagrangian finite-element model for cross-scale ocean circulation. Ocean modelling 21, 3-4 (2008), 71–96. 67, 70

[192] Zhang, Y., Meratnia, N., and Havinga, P. Adaptive and online one-class support vector machine-based outlier detection techniques for wireless sensor networks. In 2009 International Conference on Advanced Information Networking and Applications Workshops (May 2009), pp. 990–995. 110

[193] Zhang, Y., Meratnia, N., and Havinga, P. Outlier detection techniques for wireless sensor networks: A survey. Communications Surveys Tutorials, IEEE 12, 2 (Second 2010), 159–170. 28, 89, 90

[194] Zhang, Y. J., Ye, F., Stanev, E. V., and Grashorn, S. Seamless cross-scale modeling with schism. Ocean Modelling 102 (2016), 64–81. 35, 67

[195] Zhao, J., Govindan, R., and Estrin, D. Computing aggregates for monitoring wireless sensor networks. In Proceedings of the First IEEE International Workshop on Sensor Network Protocols and Applications (May 2003), pp. 139–148. 22

[196] Zhao, W., Fang, T., and Jiang, Y. Data fusion using improved dempster-shafer evidence theory for vehicle detection. In Fuzzy Systems and Knowledge Discovery, 2007. FSKD 2007. Fourth International Conference on (Aug 2007), vol. 1, pp. 487–491. 31

[197] Zhu, R. Efficient fault-tolerant event query algorithm in distributed wireless sensor networks. IJDSN 2010 (2010). 31

[198] Zhuang, P., Wang, D., and Shang, Y. Distributed faulty sensor detection. In Global Telecommunications Conference, 2009. GLOBECOM 2009. IEEE (Nov 2009), pp. 1–6. 24

[199] Zimek, A., Schubert, E., and Kriegel, H.-P. A survey on unsupervised outlier detection in high-dimensional numerical data. Statistical Analysis and Data Mining 5, 5 (Oct. 2012), 363–387. 90

[200] Zoumboulakis, M., and Roussos, G. Escalation: Complex event detection in wireless sensor networks. In Proceedings of the 2Nd European Conference on Smart Sensing and Context (Berlin, Heidelberg, 2007), EuroSSC'07, Springer-Verlag, pp. 270–285. 28

[201] Zubair, M., and Hartmann, K. Target classification based on sensor fusion in multi-channel seismic network. In Signal Processing and Information Technology (ISSPIT), 2011 IEEE International Symposium on (Dec 2011), pp. 438–443. 33