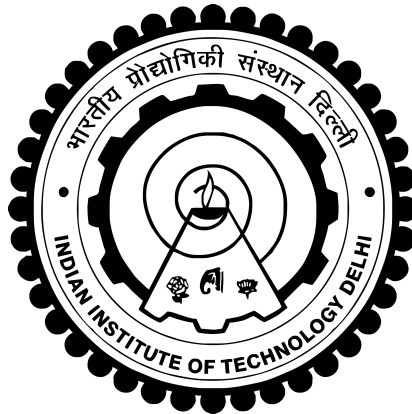


CALIBRATING SENSOR NETWORKS FOR ENVIRONMENT SENSING APPLICATION: A
SPECIFIC CASE STUDY ON CHEMICAL SENSING

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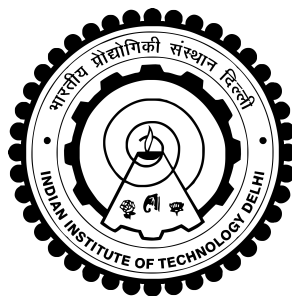
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THESIS CERTIFICATE

This is to certify that the thesis titled **Calibrating Sensor Networks for Environment Sensing Applications: A Specific Case Study On Chemical Sensing**, submitted by **Abhishek Grover**, to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy**, is a bona fide record of the research work done by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

The process of measuring physical parameters at specific locations in the geographic region is known as environment sensing. The geographic region is monitored by deploying sensors at the requisite locations. The research problems can be classified as the problems at the device-level and the problems at the network-level. At the device-level, the variations in the sensor's response due to baseline drifts and sensitivity/selectivity variations are the major problems. Two device-level algorithms have been proposed to improve the accuracy of the sensor. A time series analysis-based approach is proposed for baseline drift removal. The response of a sensor is modeled as an autoregressive (AR) process associated with an observation zero-mean Gaussian noise. The parameters of the state-space model are learned using the calibration data. The variance of the Gaussian noise is estimated using an adaptive on-line method. The AR process equation and the observation equation are used to construct the adaptive Kalman filter. Each sensor response is passed through a separate Kalman filter, and then a regression technique is used to predict the sensor response. Numerical results show that the technique is effective in removing baseline drifts in sensors. Thus for a chemical sensor, the proposed factory calibration method can help in removing baseline drifts when the sensor is deployed on the field. Adapting the observation noise variance is the key to resolving the problem of baseline drifts in sensors. The second solution consists of modelling the fluctuations in the response of a chemical sensor. A stochastic differential equation model has been proposed. The model is developed by formulating the binding and unbinding reactions in the form of Bernoulli trials. The transition probability density function (pdf) of the number of binded analyte molecules X_t , at a given time instant t , has been evaluated using the Bernoulli trial representation. The obtained pdf is used to derive the Fokker Planck equation (FPE) for the stochastic process. The FPE has a direct correspondence with the desired SDE model. A maximum a posteriori (MAP) estimation method has been proposed for evaluating the parameters. This work presents a novel theoretical contribution to the chemical sensing literature as it models the operation of a surface based chemical sensor in form of a SDE. The proposed method is useful in compensating for the effects due to sensitivity/selectivity variations. At the network level, the major issues are finding optimal locations for sensor deployment and ensuring data reliability of the network. Two network-level algorithms have been proposed as a solution to these problems. A data-driven spatio-temporal model is proposed. The spatio-temporal representation of sensor values has been modeled as the sum of a systematic trend component and a residual process. The trend component is modelled as the sum of deterministic functions, and the residual component is modelled using support vector regression. The locations with maximum support vector count in the residual model are identified as optimal for the deployment

of sensors. The method can be used for both static and dynamic deployments. The proposed method is data-driven and can be used to deploy sensors in all environment sensing applications. It only requires an initial data for the specific use case and the geographical covariates. An integro-difference equation (IDE) based spatio-temporal model is proposed for estimating missing data. The spatio-temporal field is modelled in the form of an adaptive linear state space model. The parameters of the model are identified using sensor values and are updated in a rolling window approach. Whenever missing data is encountered, the algorithm predicts the missing observations based on the learned state evolution equation. The proposed method can be used in all sensor network applications for estimating missing data as it makes no assumption about the application or on the underlying spatio-temporal field. In this thesis, the application of chemical sensing has been chosen to demonstrate the efficacy of the proposed methods. The drift correction and the deployment method has been tested on air pollution dataset. The utility of sensor modeling work is demonstrated in case of a pH sensor, molecular communication and in agent identification application. The missing data algorithm is applied on air pollution dataset and on an inertial sensor network used for human activity recognition.

KEYWORDS: Chemical Sensing, Baseline Drift Correction, Sensitivity/Selectivity variations, Sensor Deployment, Missing data

सारांश

भौगोलिक क्षेत्र में विशिष्ट स्थानों पर भौतिक मापदंडों को मापने की प्रक्रिया को पर्यावरण संवेदन के रूप में जाना जाता है। अपेक्षित स्थानों पर सेंसर लगाकर भौगोलिक क्षेत्र की निगरानी की जाती है। अनुसंधान समस्याओं को उपकरण-स्तर पर समस्याओं और नेटवर्क-स्तर पर समस्याओं के रूप में वर्गीकृत किया जा सकता है। डिवाइस-स्तर पर, बेसलाइन ड्रिफ्ट्स और संवेदनशीलता/चयनात्मकता भिन्नताओं के कारण सेंसर की प्रतिक्रिया में बदलाव प्रमुख समस्याएं हैं। सेंसर की सटीकता में सुधार के लिए दो डिवाइस-स्तरीय एल्गोरिदम प्रस्तावित किए गए हैं। आधारभूत बहाव को हटाने के लिए एक समय श्रृंखला विश्लेषण-आधारित दृष्टिकोण प्रस्तावित है। एक सेंसर की प्रतिक्रिया एक ऑटोरेग्रेसिव (एआर) प्रक्रिया के रूप में तैयार की जाती है जो एक अवलोकन शून्य-माध्य गाऊसी शोर से जुड़ी होती है। अंशांकन डेटा का उपयोग करके राज्य-अंतरिक्ष मॉडल के मापदंडों को सीखा जाता है। एक अनुकूली ऑनलाइन पद्धति का उपयोग करके गाऊसी शोर के विचरण का अनुमान लगाया जाता है। एआर प्रक्रिया समीकरण और अवलोकन समीकरण का उपयोग अनुकूली कलमन फिल्टर के निर्माण के लिए किया जाता है। प्रत्येक सेंसर प्रतिक्रिया को एक अलग कलमन फिल्टर के माध्यम से पारित किया जाता है, और फिर सेंसर प्रतिक्रिया की भविष्यवाणी करने के लिए एक प्रतिगमन तकनीक का उपयोग किया जाता है। संख्यात्मक परिणाम बताते हैं कि सेंसर में बेसलाइन ड्रिफ्ट को हटाने में तकनीक प्रभावी है। इस प्रकार एक रासायनिक सेंसर के लिए, प्रस्तावित फ्रैक्टरी कैलिब्रेशन विधि बेसलाइन ड्रिफ्ट को हटाने में मदद कर सकती है जब सेंसर को मैदान पर तैनात किया जाता है। सेंसर में बेसलाइन ड्रिफ्ट की समस्या को हल करने के लिए अवलोकन शोर विचरण को अपनाया महत्वपूर्ण है। दूसरे समाधान में रासायनिक सेंसर की प्रतिक्रिया में उतार-चढ़ाव की मॉडलिंग शामिल है। एक स्टोकेस्टिक अंतर समीकरण मॉडल प्रस्तावित किया गया है। मॉडल को बर्नौली परीक्षणों के रूप में बाध्यकारी और अनबाइंडिंग प्रतिक्रियाओं को तैयार करके विकसित किया गया है। बर्नौली परीक्षण प्रतिनिधित्व का उपयोग करके किसी निश्चित समय तत्काल t पर, बाध्य विश्लेषक अणुओं की संख्या X_t के संक्रमण संभाव्यता घनत्व फंक्शन (पीडीएफ) का मूल्यांकन किया गया है। प्राप्त पीडीएफ का उपयोग स्टोकेस्टिक प्रक्रिया के लिए फोककर प्लैंक समीकरण (एफपीई) प्राप्त करने के लिए किया जाता है। एफपीई का वांछित एसडीई मॉडल के साथ सीधा पत्राचार है। मापदंडों के मूल्यांकन के लिए एक अधिकतम एपोस्टीरियरी (एमएपी) अनुमान पद्धति का प्रस्ताव किया गया है। यह काम रासायनिक संवेदन साहित्य में एक उपन्यास सैद्धांतिक योगदान प्रस्तुत करता है क्योंकि यह एक एसडीई के रूप में सतह आधारित रासायनिक सेंसर के संचालन को मॉडल करता है। प्रस्तावित विधि संवेदनशीलता/चयनात्मक भिन्नताओं के कारण होने वाले प्रभावों की क्षतिपूर्ति करने में उपयोगी है। नेटवर्क स्तर पर, प्रमुख मुद्दे सेंसर परिनियोजन के लिए इष्टतम स्थान ढूंढ रहे हैं और नेटवर्क की डेटा विश्वसनीयता सुनिश्चित कर रहे हैं। इन समस्याओं के समाधान के रूप में दो नेटवर्क-स्तरीय एल्गोरिदम प्रस्तावित किए गए हैं। एक डेटा-संचालित अनुपात-अस्थायी मॉडल प्रस्तावित है। सेंसर मूल्यों के अनुपात-अस्थायी प्रतिनिधित्व को एक व्यवस्थित प्रवृत्ति घटक और एक अवशिष्ट प्रक्रिया के योग के रूप में तैयार किया गया है। प्रवृत्ति घटक को नियतात्मक कार्यों के योग के रूप में तैयार किया गया है, और अवशिष्ट घटक को समर्थन वेक्टर प्रतिगमन का उपयोग करके तैयार किया गया है। अवशिष्ट मॉडल में अधिकतम सपोर्ट वेक्टर काउंट वाले स्थानों को सेंसर लगाने के लिए इष्टतम के रूप में पहचाना जाता है। विधि का उपयोग स्थिर और गतिशील दोनों परिनियोजन के लिए किया जा सकता है। प्रस्तावित विधि डेटा-चालित है और इसका उपयोग सभी पर्यावरण संवेदन अनुप्रयोगों में सेंसर लगाने के लिए किया जा सकता है। इसके लिए केवल विशिष्ट उपयोग के मामले और भौगोलिक सहसंयोजकों के लिए एक प्रारंभिक डेटा की

आवश्यकता होती है। लापता डेटा का अनुमान लगाने के लिए एक पूर्णांक-अंतर समीकरण (आईडीई) आधारित अनुपात-अस्थायी मॉडल प्रस्तावित है। अनुपात-अस्थायी क्षेत्र को एक अनुकूली रैखिक राज्य अंतरिक्ष मॉडल के रूप में तैयार किया गया है। मॉडल के मापदंडों को सेंसर मानों का उपयोग करके पहचाना जाता है और रोलिंग विंडो दृष्टिकोण में अद्यतन किया जाता है। जब भी लापता डेटा का सामना करना पड़ता है, तो एल्गोरिथम सीखे गए राज्य विकास समीकरण के आधार पर लापता टिप्पणियों की भविष्यवाणी करता है। प्रस्तावित विधि का उपयोग सभी सेंसर नेटवर्क अनुप्रयोगों में लापता डेटा का अनुमान लगाने के लिए किया जा सकता है क्योंकि यह आवेदन के बारे में या अंतर्निहित स्थानिक-अस्थायी क्षेत्र पर कोई धारणा नहीं बनाता है। इस थीसिस में प्रस्तावित विधियों की प्रभावकारिता को प्रदर्शित करने के लिए रासायनिक संवेदन के अनुप्रयोग को चुना गया है। वायु प्रदूषण डेटासेट पर बहाव सुधार और परिनियोजन विधि का परीक्षण किया गया है। एक पीएच सेंसर, आणविक संचार और एजेंट पहचान आवेदन के मामले में सेंसर मॉडलिंग कार्य की उपयोगिता का प्रदर्शन किया जाता है। लापता डेटा एल्गोरिदम वायु प्रदूषण डेटासेट और मानव गतिविधि पहचान के लिए उपयोग किए जाने वाले एक जड़त्वीय सेंसर नेटवर्क पर लागू होता है।

Contents

| | |
|--|-----------|
| ACKNOWLEDGEMENTS | 1 |
| ABSTRACT | 2 |
| LIST OF FIGURES | 9 |
| LIST OF TABLES | 10 |
| ABBREVIATIONS | 11 |
| 1 INTRODUCTION | 13 |
| 1.1 Environment sensing: Applications and Challenges | 13 |
| 1.2 The specific case: Chemical sensing | 15 |
| 1.3 A brief note on calibration | 16 |
| 1.4 Literature Review | 17 |
| 1.4.1 Baseline drift correction | 17 |
| 1.4.2 Fluctuation sensing | 19 |
| 1.4.3 Sensor deployment | 21 |
| 1.4.4 Missing data estimation | 25 |
| 1.5 Motivation, Objectives and Scope | 27 |
| 1.5.1 Motivation | 27 |
| 1.5.2 Objectives | 28 |
| 1.5.3 Scope | 28 |
| 1.6 Thesis outline | 29 |
| 2 A Method for Removing Baseline Drifts in Chemical Sensors | 30 |
| 2.1 Time Series Analysis | 30 |
| 2.2 Kalman Filter | 32 |
| 2.3 Sensor Calibration | 34 |

| | | |
|----------|--|-----------|
| 2.3.1 | Preprocessing | 36 |
| 2.3.2 | System Identification | 36 |
| 2.3.3 | Online Parameter Estimation | 38 |
| 2.3.4 | Multivariate Regression | 40 |
| 2.4 | Results | 41 |
| 2.4.1 | Data and Statistical Tools | 41 |
| 2.4.2 | Numerical Results | 43 |
| 2.4.3 | Comparison | 47 |
| 2.5 | Concluding Remarks | 50 |
| 3 | A Stochastic Model for Characterizing Fluctuations in Chemical Sensing | 51 |
| 3.1 | Wiener Process | 51 |
| 3.2 | Stochastic Differential Equation | 52 |
| 3.3 | Stochastic Model for Chemical Sensing | 53 |
| 3.4 | Parameter Estimation For Binding-Unbinding Kinetics | 61 |
| 3.5 | Spectrum Estimation using SDE | 63 |
| 3.6 | Numerical Results | 67 |
| 3.6.1 | An experimental setup to analyze the response of an adsorption based chemical sensor | 67 |
| 3.6.2 | Simulation analysis of noise in the receiver system used in molecular communication | 70 |
| 3.6.3 | Fluctuation enhanced sensing in chemical sensors | 73 |
| 3.7 | Concluding Remarks | 77 |
| 4 | A Data-Driven Framework for Deploying Sensors | 78 |
| 4.1 | Framework for Optimal Deployment of Sensors | 79 |
| 4.1.1 | Mean Process Modeling | 80 |
| 4.1.2 | Geographical Covariates | 83 |
| 4.1.3 | Residual Modelling | 83 |
| 4.1.4 | Deployment Strategy | 86 |
| 4.1.5 | Dynamic Deployment | 87 |
| 4.2 | Results | 88 |

| | | |
|----------|--|------------|
| 4.2.1 | Data | 88 |
| 4.2.2 | Leave-One-Out Cross-Validation | 89 |
| 4.2.3 | Subset Cross-Validation | 91 |
| 4.3 | Comparison | 92 |
| 4.4 | Concluding Remarks | 96 |
| 5 | A Recursive Method for Estimating Missing Data | 97 |
| 5.1 | Integro-difference equations (IDE) | 97 |
| 5.2 | Karhunen-Loève expansion | 98 |
| 5.3 | State Space Model for Spatio-temporal Field | 99 |
| 5.3.1 | State Space Model | 99 |
| 5.3.2 | Convergence | 105 |
| 5.3.3 | Online Observation Noise Estimation | 106 |
| 5.4 | Missing Data Estimation | 108 |
| 5.5 | Numerical Results | 111 |
| 5.6 | Comparison | 115 |
| 5.6.1 | Missing data estimation on air quality dataset | 117 |
| 5.6.2 | Missing data estimation on inertial sensor network dataset | 118 |
| 5.7 | Concluding Remarks | 119 |
| 6 | Conclusion and Future Scope | 120 |
| 6.1 | Conclusion | 120 |
| 6.2 | Future scope | 121 |
| 6.3 | Summary | 122 |

List of Figures

| | | |
|-----|---|----|
| 2.1 | Calibration model; KF1, KF2, KF3, KF4 and KF5 are Kalman filters for each sensor signal. $C(t)$ is the predicted concentration at time instant t | 35 |
| 2.2 | Sensor signal model | 36 |
| 2.3 | Log transformed time series of sensor responses for the five sensors used in sensor array. The blue times series corresponds to the original sensor responses and the black sensor responses corresponds to the filtered sensor response. (a) PT08.S1.CO (b) PT08.S2.NMHC (c) PT08.S3.NOx (d) PT08.S4.NO2 (e) PT08.S5.O3. The notations for sensors corresponds to the ones used in UCI dataset [1] | 43 |
| 2.4 | Comparison of hourly average MAE on weekly basis between Prediction model using only MVLN (black) and Prediction model using Kalman filter bank followed by MVLN (red) for all pollutants (a) CO (b) C ₆ H ₆ (c) NOx (d) NO ₂ . The value of $\alpha = 0.002$ was used for this result. | 44 |
| 2.5 | Log transformed time series of sensor responses for the five sensors used in sensor array. The black time series corresponds to the original sensor responses. (a)-(e) Drift corrected waveform (green) using baseline removal method (D1), (f)-(j) Drift corrected waveform (yellow) using DWT method (D2), (k)-(o) Drift corrected waveform (orange) using OSC method (D3). | 48 |
| 3.1 | A schematic for depicting dynamics of the analyte molecules at the sensor surface. The binded molecules are closest to the sensor surface. | 55 |
| 3.2 | Experimental setup to analyze response of a chemical sensor (a) Experimental setup (b) Block Diagram | 68 |
| 3.3 | (a) Voltage response of the electrode for a period of 250s (b) Voltage response for the interval 30s-45s (c) pH values for a period of 250s (d) Power spectrum for the volatge waveform in (a) | 69 |
| 3.4 | Number of ambient analyte molecules ($c_R(t)$) in the receptor space of the receiver. | 70 |
| 3.5 | Number of binded molecules (X_t) on the sensor surface | 71 |
| 3.6 | Fluctuations (R_t) in the number of binded molecules on the sensor surface | 71 |
| 3.7 | Power spectral density of the fluctuations in the number of binded molecules on the sensor surface | 72 |

| | | |
|------|--|-----|
| 3.8 | Comparison of the number of binded molecule waveform and the fluctuation waveform for various values of forward and reverse reaction constants.(a),(b) $k_f = 0.1, k_b = 10$.(c),(d) $k_f = 0.01, k_b = 10$ | 72 |
| 3.9 | Sensor conductance values for the complete duration of a specific experiment in the dataset. | 74 |
| 3.10 | Normalized conductance Y_k^s simulated using the SDE in (3.35). The parameters for the SDE have been learned using the specific case in figure 3.9. . . | 75 |
| 3.11 | Power spectral density of sensor fluctuations | 75 |
| 3.12 | Confusion matrices for the classification experiment with features: (a) Time domain features from all 8 sensors (b) Frequency domain features from all sensors (c) Time domain and frequency domain features from all sensors . | 76 |
| 4.1 | Data assimilation from sensing network and pollution models; 'M' denotes sensors in a network | 80 |
| 4.2 | Steps for finding optimal locations for sensor deployment | 81 |
| 4.3 | A map depicting the location of pollution monitoring sites in Greater London Region | 89 |
| 4.4 | Results for leave-one-out cross-validation. (a) Locations with highest support vector data points marked with red indicator. The dotted line indicates the average RMSE value. (b) Top 10 locations with maximum inter-sensor distance marked with green indicator (c) Top 10 locations with maximum euclidean distance in the feature vector space marked with orange indicator | 90 |
| 4.5 | Results for subset cross-validation in concentration levels; (a) Log concentration levels (b) Actual Concentration levels. The y-axis represents the RMSE error and the x-axis represents the index of subset used for building the model. | 91 |
| 4.6 | Results for the classical experimental design based deployment method (a) Training set leave-one-out, (b) Test set leave-one-out, (c) Training set subset-cross-validation and (d) Test set subset-cross-validation | 93 |
| 4.7 | Results for the mutual information based deployment method (a) leave-one-out and (b) subset cross-validation | 94 |
| 4.8 | Results for the Machine learning based deployment method (a) Training set leave-one-out, (b) Test set leave-one-out, (c) Training set subset-cross-validation and (d) Test set subset-cross-validation | 95 |
| 5.1 | Flowchart for the algorithm proposed in this study; KF:Kalman Filter . . . | 100 |
| 5.2 | (a) Density histogram and density function for error values ; $p = 0.2, k = 1$ (b) Spatial variation in MARE; $p = 0.2, k = 1$ | 112 |
| 5.3 | Temporal variation in MARE for sites indexed (a)1-6, (b)7-12, (c)13-18, (d)19-24, (e)25-30, (f)31-36, (g)37-42, (h)43-48, (i)49-53; For all cases (a)-(i): $p = 0.2, k = 1$ | 114 |

| | | |
|-----|--|-----|
| 5.4 | (a) Density curve of ARE for varying missing probability rate; $k = 1$; C1: $p = 0.1$, C2: $p = 0.2$, C3: $p = 0.3$, C4: $p = 0.4$ (b) Density curve of ARE for varying number of missing observations at a single time instant; $p = 0.2$; C1: $k = 2$, C2: $k = 4$, C3: $k = 8$, C4: $k = 1 : 8$ | 115 |
| 5.5 | Comparison among density curves of ARE in prediction estimates from algorithms: IDE, KNN, GP, SVT, SVR, LSTM, KFST, RM | 117 |
| 5.6 | Comparison among density curves of ARE for the inertial sensors dataset; (a) acceleration in x direction, (b) acceleration in y direction, (c) acceleration in z direction | 118 |

List of Tables

| | | |
|-----|---|-----|
| 1.1 | Literature review for the problems studied in this thesis | 26 |
| 2.1 | Error parameters using only pattern recognition techniques; M1: SVR, M2: PLS, M3: MVLR | 41 |
| 2.2 | Error parameters using proposed calibration model for $\alpha = 0.001$, $\alpha = 0.002$, and $\alpha = 0.003$; Three pattern recognition techniques (M1: SVR, M2: PLS, M3: MVLR) were used for analysis. | 42 |
| 2.3 | Hourly average MAE in initial and final phase of sensor deployment. Phase 1 represents the initial 20 weeks and phase 2 represents the last 19 weeks. CM1 is the MAE using only pattern recognition techniques and CM2 is the MAE for proposed calibration model. | 45 |
| 2.4 | Comparison between training set lengths 300 hrs (Interval 1) and 700 hrs (Interval 2) | 47 |
| 2.5 | Prediction accuracy results for other drift correction methods; D1: Baseline Removal using FFT, D2: Discrete Wavelet Transform, D3: Orthogonal Signal Correction | 47 |
| 3.1 | Classification accuracy (%) using the proposed frequency domain and time domain features as input for the classification algorithm | 76 |
| 4.1 | Two sets of Hyperparameters used in SVR | 86 |
| 5.1 | Comparison among computation time and memory requirements for algorithms: IDE, KNN, GP, SVT, SVR, LSTM, KFST | 117 |
| 6.1 | Research gaps and the solutions proposed in this thesis | 121 |
| 6.2 | Applicability and limitations of the proposed methods | 122 |

ABBREVIATIONS

| | |
|-------------|----------------------------------|
| WSN | Wireless Sensor Network |
| SNR | Signal to Noise Ratio |
| SVM | Support Vector Machine |
| SVR | Support Vector Regression |
| KF | Kalman Filter |
| PCA | Principal Component Analysis |
| PLS | Partial Least Squares |
| RMSE | Root Mean Square Error |
| MAE | Mean of Absolute Error |
| R | R programming language |
| FFT | Fast Fourier Transform |
| DWT | Discrete Wavelet Transform |
| OSC | Orthogonal Signal Correction |
| SDE | Stochastic Differential Equation |
| PDF | Probability Density Function |
| FPE | Fokker Planck Equation |
| ODE | Ordinary Differential Equation |
| PSD | Power Spectral Density |
| MAP | Maximum A posteriori |
| FES | Fluctuation Enhanced Sensing |
| SP | Signal Processing |
| TSA | Time Series Analysis |
| LRK | Ligand-Receptor Kinetics |
| ET | Estimation Theory |
| GT | Geometric Techniques |
| MBT | Model-Based Techniques |
| SC | Spatial Correlation |
| LR | Low-Rank based methods |
| DL | Deep Learning |
| SSM | State Space Models |
| RHS | Right Hand Side |
| LHS | Left Hand Side |
| pH | Potential of Hydrogen |
| ST | Spatio-Temporal |

| | |
|-------------|--|
| CFD | Computational Fluid Dynamics |
| RF | Radio Frequency |
| LUR | Land Use Regression |
| SVD | Singular Value Decomposition |
| SEOF | Smooth Empirical Orthogonal Functions |
| IDE | Integro-Difference Equation |
| KLT | Karhunen Loeve Theorem |
| EM | Expectation Maximization |
| MARE | Mean of Absolute Relative Error |
| ARE | Absolute Relative Error |
| KNN | K-Nearest Neighbour |
| GP | Gaussian Process |
| SVT | Singular Value Thresholding |
| LSTM | Long-Short Term Memory |
| KFST | Kalman Filter-based Spatio Temporal Regression |
