

**FRUGAL SENSING AND COMPUTE
USING AI/ML
FOR URBAN SUSTAINABILITY**

SACHIN KUMAR CHAUHAN



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY DELHI
JULY 2025**

© Indian Institute of Technology Delhi (IITD), New Delhi, 2025

FRUGAL SENSING AND COMPUTE USING AI/ML FOR URBAN SUSTAINABILITY

by

SACHIN KUMAR CHAUHAN

Department of Computer Science and Engineering

Submitted

in fulfillment of the requirements of the degree of **Doctor of Philosophy**

to the



Indian Institute of Technology Delhi

July 2025

To Everyone in the Past, Present and Future

For making me exist and pursue a PhD in a small moment of the grand time.

Certificate

This is to certify that the thesis titled **Frugal Sensing and Compute using AI/ML for Urban Sustainability**, submitted by **Mr. Sachin Kumar Chauhan**, to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy** in Computer Science & Engineering, is a record of bonafide work carried out by him under my guidance and supervision at the Department of Computer Science & Engineering, Indian Institute of Technology Delhi. The contents of this thesis, in full or in parts, have not been submitted elsewhere for the award of any degree or diploma.

Dr Rijurekha Sen

Professor

Dept. of Computer Science and Engineering

Indian Institute of Technology Delhi

New Delhi-110016

Acknowledgements

If you want to shine like a sun, first burn like a sun.

– A.P.J. Abdul Kalam

I express my gratitude to all those who have supported and guided me throughout the journey of my research for this thesis. I would like to begin by conveying my deepest gratitude to my supervisor, Dr. Rijurekha Sen, for her invaluable guidance and encouragement throughout the research tenure. I am profoundly thankful for her insightful feedback and unwavering support in shaping this thesis. I wish to extend my thanks to Prof Sayan Ranu for his unconditional guidance and mentorship for the pollution measurement and sensor placement problems. His calm and thoughtful questions were another inspiring source of deeper analysis and experimentation before reaching a conclusion.

I also thank the members of my advisory committee (SRC), Prof Mausam, Prof Srikanta Bedathur, Prof Subhashis Banerjee, and Prof Shubhendu Bhasin, whose constructive comments and suggestions helped to improve the quality of my work. I acknowledge the in-depth teaching and discussions by the Professors of the courses undertaken, that formed the foundation of my research in an emerging technology. I am indebted to the department, all Professors, support staff and my colleagues for fostering the supportive and research-friendly culture.

I would also like to acknowledge the help of all my research collaborators, and other institutions - Aabmatica Technologies, SERB, EDF, DIMTS, WBTC, WBPCB, DPCC - for supporting me in field deployments of our sensors and aiding data collection, without which important parts and analysis of this thesis would not be possible.

Finally, it is never last to acknowledge the enduring faith and support of the family in the long tenure of doctoral research, without which this enriching journey might have been arduous and less fulfilling.

This thesis represents not just a culmination of my doctoral research but also the many personal lessons learned along the way. The journey has been one of growth, patience, and resilience, all of which has shaped me into a better version of myself.

Those who can imagine anything, can create the impossible.

– Alan Turing

Sachin Kumar Chauhan

Abstract

The Industrial Revolution was a turning point in human history which influenced almost every aspect of life. This has improved the human way of living in many ways, but has also induced many negative side effects on human society at large. While the advancement of sophisticated technologies for transport of people and goods, and the efficient processing in the factories, pave way to reduce many scarcities, the congestion on the roads and the induced air/water/noise pollution impacted the humans in a drastic way. With the recent explosion in populations across countries, the consumption of goods and services have never been so high, and the side effects of the development are worse than never before.

Various governmental and public institutions around the world, supported by researchers and domain experts, have been working hard to reduce such side-effects. With the two problems of air pollution and traffic congestion being highly interlinked, they are commonly studied and analyzed together [1, 2, 3, 4, 5, 6, 7, 8] and are practically associated [9, 10, 11]. In the era of AI/ML, the efforts to improve the detection and mitigate the extreme impacts got a new direction. Sophisticated AI methods can help us detect the causes and effects of pollution indicating the authorities to act sooner. Newer AI based solutions can emerge to solve the traffic congestion leading to effective transportation. These solutions need an array of sensing devices alongside high computation requirements. The deployments of such AI based solutions on a large scale would cost highly. While developed nations can invest heavily on these solutions, the large part of humanity living under developing and under-developed economies could not scale on the costly advancements.

In this work, we aim to improve the situation of deploying the AI advancements at scale in the under-developed economies by providing frugal, i.e. efficient and cost-effective, solution approaches to the societal problems of air pollution analysis & mitigation and traffic congestion control using limited sensing devices and efficient computing. AI solutions that need less sensors and limited compute can be effectively deployed on low-cost edge devices, allowing the scaled deployment feasible for countries with limited budget.

Abstract

औद्योगिक क्रांति मानव इतिहास में एक महत्वपूर्ण मोड़ थी जिसने जीवन के लगभग हर पहलू को प्रभावित किया। इसने कई तरह से मानव जीवन जीने के तरीके को बेहतर बनाया है, लेकिन इसने मानव समाज पर कई नकारात्मक दुष्प्रभाव भी डाले हैं। जहाँ लोगों और वस्तुओं के परिवहन और कारखानों में कुशल प्रसंस्करण के लिए परिष्कृत तकनीकों की उन्नति ने कई अभावों को कम करने का मार्ग प्रशस्त किया, वहीं सड़कों पर भीड़भाड़ और प्रेरित वायु/जल/ध्वनि प्रदूषण ने मनुष्यों को बहुत ज़्यादा प्रभावित किया। हाल ही में विभिन्न देशों में जनसंख्या में हुए विस्फोट के साथ, वस्तुओं और सेवाओं की खपत पहले कभी इतनी अधिक नहीं रही, और विकास के दुष्प्रभाव पहले से कहीं ज़्यादा खराब हैं।

शोधकर्ताओं और डोमेन विशेषज्ञों द्वारा समर्थित दुनिया भर के विभिन्न सरकारी और सार्वजनिक संस्थान ऐसे दुष्प्रभावों को कम करने के लिए कड़ी मेहनत कर रहे हैं। वायु प्रदूषण और यातायात भीड़भाड़ की दो समस्याओं के आपस में अत्यधिक जुड़े होने के कारण, उनका आमतौर पर अध्ययन और विश्लेषण एक साथ किया जाता है और व्यावहारिक रूप से वे एक दूसरे से जुड़े हुए हैं। AI/ML के युग में, पता लगाने में सुधार करने और चरम प्रभावों को कम करने के प्रयासों को एक नई दिशा मिली है। परिष्कृत AI विधियाँ हमें प्रदूषण के कारणों और प्रभावों का पता लगाने में मदद कर सकती हैं, जिससे अधिकारियों को जल्द ही कार्रवाई करने का संकेत मिलता है। यातायात भीड़भाड़ को हल करने के लिए नए AI आधारित समाधान सामने आ सकते हैं, जिससे प्रभावी परिवहन हो सकता है। इन समाधानों के लिए उच्च संगणना आवश्यकताओं के साथ-साथ संवेदन उपकरणों की एक सरणी की आवश्यकता होती है। बड़े पैमाने पर ऐसे AI आधारित समाधानों की तैनाती में बहुत अधिक लागत आएगी। जबकि विकसित देश इन समाधानों पर भारी निवेश कर सकते हैं, विकासशील और अविकसित अर्थव्यवस्थाओं में रहने वाली मानवता का बड़ा हिस्सा महंगी प्रगति का लाभ नहीं उठा सकता है।

इस कार्य में, हमारा उद्देश्य सीमित संवेदन उपकरणों और कुशल कंप्यूटिंग का उपयोग करके वायु प्रदूषण विश्लेषण व शमन और यातायात भीड़ नियंत्रण की सामाजिक समस्याओं के लिए किफायती, यानी कुशल और लागत प्रभावी समाधान दृष्टिकोण प्रदान करके अल्प-विकसित अर्थव्यवस्थाओं में बड़े पैमाने पर AI उन्नति को लागू करने की स्थिति में सुधार करना है। AI समाधान जिन्हें कम सेंसर और सीमित कंप्यूटिंग की आवश्यकता होती है, उन्हें कम लागत वाले Edge डिवाइस पर प्रभावी ढंग से तैनात किया जा सकता है, जिससे सीमित बजट वाले देशों के लिए बड़े पैमाने पर तैनाती संभव हो सके।

Contents

Certificate	i
Acknowledgements	iii
Abstract	v
LIST OF TABLES	xvi
LIST OF FIGURES	xxii
1 INTRODUCTION	1
1.1 Contributions	4
2 CREATING POLLUTION DATASETS TO FEED TO AI/ML PROBLEMS	7
2.1 Introduction	7
2.1.1 Related Work	10
2.1.2 Questions analysed	11
2.2 System Architecture : Web of Low Cost Particulate Matter Sensors	12
2.3 Dataset Collection Challenges	13
2.4 Data Quality Analysis	15

2.4.1	Anova Tests Analysis for Low Cost Sensor (LCS)	17
2.5	Need for calibrating the LCS data	21
2.5.1	Preprocessing dataset for analysis	22
2.5.2	Dataset Statistics	22
2.5.3	Meteorological Factors (Temperature, Relative Humidity, Wind Speed) Analysis	23
2.5.4	Spatio-temporal Correlation and Covariance Analysis	25
2.6	Low Cost Sensor Calibration	28
2.7	ML Interpolation & Forecasting Modeling Benchmarks	33
2.7.1	Formulation of different ML Prediction Problems	33
2.7.2	ML Algorithms Benchmarked	33
2.7.3	Graphsage (with Graph formulation)	34
2.8	Dataset Pre-processing and Evaluation Metrics for the Analysis	36
2.9	Observations and Inferences	37
2.10	Conclusion	42
3	USING AI/ML TO RECOMMEND POLLUTION SENSOR LOCATIONS	43
3.1	Introduction	43
3.1.1	Related work	45
3.1.2	Questions analysed	46
3.2	Empirical motivation for AIRSHOT	46
3.2.1	Patterns observed in PM dataset	47
3.2.2	Regional Patterns in PM	47
3.2.3	Hyper-local Patterns in PM	48

3.2.4	Seasonal influence on Hyperlocal Patterns	49
3.2.5	Implications on CAAQMS placement	49
3.3	Location recommendation algorithm	51
3.3.1	Sensor Placement Problem Formulation	51
3.3.2	RLSELECT algorithm	52
3.4	AIRSHOT Evaluation	55
3.4.1	Data Splits	55
3.4.2	Location recommendation baselines	56
3.4.3	Effect of feature selection	57
3.4.4	Effect of increasing temporal data	57
3.4.5	Effect of recommendation algorithm	59
3.4.6	Evaluation with other PM datasets	59
3.4.7	Evaluation with precipitation dataset	61
3.4.8	Forecasting	61
3.5	Conclusion	62
4	USING AI/ML TO CONTROL TRAFFIC CONGESTION AT INTERSECTIONS	63
4.1	Introduction	63
4.1.1	Related work	66
4.1.2	Questions analysed	67
4.2	Real Data Description	68
4.2.1	Data Collection Challenges	68
4.2.2	Dataset Processing	69
4.2.3	Dataset Quality	70

4.2.4	Dataset Uniqueness	72
4.3	Need for Intelligent Traffic Light Control	74
4.3.1	Problem Definition	74
4.4	FRUGALLIGHT	75
4.4.1	Design Prerequisites	76
4.4.2	FRUGALLIGHT DRL Architecture	77
4.4.3	FRUGALLIGHT Rewards	78
4.4.4	DRL compression using domain knowledge	78
4.5	FRUGALLIGHT Evaluation	81
4.5.1	Baselines	81
4.5.2	Benchmarks	81
4.5.3	Simulator	81
4.5.4	DRL Efficiency	82
4.5.5	FL performance on existing open-source datasets	83
4.5.6	FL performance on our New Delhi dataset	86
4.6	Enhanced FRUGALLIGHT	87
4.6.1	Student-teacher knowledge distillation, with FRUGALLIGHT's domain knowledge	87
4.6.2	FRUGALLIGHT's Transferability and Adaptability	89
4.6.3	Enhanced Adaptability using Gradient based Meta Learning (MAML) .	90
4.6.4	Doing Away with Runtime DRL: Lookup Table based Intersection Control (Goodness EcoLight)	91
4.6.5	Doing Away With Look-up Tables: Threshold based Intersection Control (Threshold EcoLight)	95

4.7	Input to Control Algorithms: Computer Vision for End-To-End System	99
4.8	Conclusion	100
5	CONCLUSION AND FUTURE WORK	101
5.1	Limitations and Future Work	102
	Bibliography	105
	List of Publications	123
	Biography	125

List of Tables

2.1	Two-way ANOVA test for DustTrak Reference Sensor vs Our Low Cost Sensor Mobile Sensor 1	18
2.2	One-way ANOVA test for DustTrak Reference Sensor vs Our Low Cost Sensor Mobile Sensor 1	19
2.3	Two-way ANOVA test for Our Low Cost Sensor Mobile Sensor 1 vs 2	19
2.4	One-way ANOVA test for Our Low Cost Sensors Colocated at Bidhannagar (BN) and Cossipore (CP), Kolkata	20
2.5	Details of Kolkata (India), Delhi-NCR (India). Hamilton, Ontario (Canada) and USA datasets. Delhi-NCR and Kolkata datasets show high standard deviation. .	22
2.6	Correlation of Temperature, RH and WS with PM values.	23
2.7	Calibration RMSE Error for different algorithms for Delhi dataset.	31
2.8	Run-time (in seconds) for different interpolation algorithms.	39
3.1	Spatial correlations of low-cost sensor locations in the Spring and Autumn season.	48
3.2	Interpolation Task RMSE on adding one CAAQMS location to the existing three CAAQMS sensors. Bold values beside up-arrows show increase in RMSE on adding new sensor.	50

3.3	Interpolation RMSE on seasonal test data using seasonal or combined training data, for different algorithms recommending 5 sensor locations. Respective season's training data is required for good performance (in bold) over that season's test data. For good performance, we can use separate algorithm-model for each season or a single algorithm-model for all seasons. .	58
4.1	Train and test data for YOLO V2 and Tiny-YOLO	71
4.2	Accuracy-vs-latency trade-off of CNN models	71
4.3	Open source real traffic datasets.	73
4.4	DNN properties	82
4.5	Model property for 4approach x 3lane intersection	82
4.6	Properties for Baseline NonRL Algorithms	82
4.7	Performance on different duration 1x1 developing region data (total time @ throughput)	86
4.8	Knowledge distillation (total time @ throughput). Peers (same row in bold) teach better than PL (in <i>italics</i>).	88
4.9	Transfer to other dataset for ExploredLearn models.	89
4.10	Performance of Goodness EcoLight for average case metrics	94
4.11	Performance of Goodness EcoLight for worst case (fairness) metrics for 16x3 .	94
4.12	Algorithm Hyper Parameters	96
4.13	Empirically Learnt Values	96
4.14	Performance of EcoLight Thresholding Algorithms for average case metrics . .	97
4.15	Performance of Threshold EcoLight for worst case (fairness) metrics for 16x3 .	98
4.16	Performance on other 1x1 datasets	98

List of Figures

1.1	Low-Cost Pollution Sensors deployed at School rooftop and inside buses, Traffic Cameras deployed on poles at the intersection. Image Source: ChatGPT (DALL-E).	3
2.1	Web of low-cost PM _{2.5} sensors system architecture in (a) and screenshots from the web based dashboard in (b)-(c).	12
2.2	(a) Inside of our PM measuring IoT unit. (b) Mounting location in bus driver's cabin in non air-conditioned public bus (below the existing white box). (c) Government deployed static sensors installed in and around our bus trajectories, as location icons.	14
2.3	(a) PM _{2.5} values measured by our low-cost mobile PM sensors (USD 30) vs. TSI DustTrak (USD 9500) between Jul 21-31, 2021. (b) Mean Difference and (d) Histogram of pointwise differences of PM _{2.5} values measured by DustTrak and low cost mobile PM sensors. (c) Histogram of PM _{2.5} in the intervals on x-axis. The values are almost identical.	15
2.4	Distribution of PM _{2.5} collected by our low-cost sensor and gold standard sensor over 7 random days. The distributions are similar across the two sets of instruments.	16
2.5	Mean and Standard Deviation for DustTrak and our Low Cost Mobile sensors. .	18

2.6	(a) Pollution Sensor placements in Kolkata region. CAAQMS sensors are in Black, whereas our Low Cost Static Sensors are in Green. S23 is down due to installation issues and hence not considered. The traces in red/orange/yellow colours depict the trajectories covered by different buses having our low cost mobile sensors. Red colour depict high $PM_{2.5}$ whereas orange/yellow depict relatively lower $PM_{2.5}$. Also, thinner traces depict less number of samples (less bus travel) and bigger traces depict high number of samples (frequent bus travel). (b) Number of hourly samples available in the datasets (Y-axis) for different low-cost sensors (X-axis) in the three seasons. As Winter set has more days, relatively more data is available for Winter. Some sensors are facing power / network connection / maintenance issues and hence less data is available for such sensors. Also, mobile devices are added to buses in a phased manner, so winter has more mobile devices than other seasons.	20
2.7	CAAQMS vs LCS data for an arbitrary day (Dec 15, 2023).	21
2.8	Meteorological factors vs $PM_{2.5}$ over the 3 months. The orange vertical lines show the relation of high or low $PM_{2.5}$ with WS, temperature and RH. The red box shows the situation of very high $PM_{2.5}$ which is explained with non-meteorological causes.	24
2.9	autocorrelation for 12 grid locations for 1 hour lag (the titles contain the latitude-longitude of the grid locations).	25
2.10	Autocorrelation for 12 grid locations up to 1.5 days lags.	26
2.11	Autocorrelation for A and C grid locations for up to 7 days lags. The autocorrelation decreases with increasing the lag.	26
2.12	Autocorrelation for A and C grid locations for up to 7 days lags as heat-map. The autocorrelation decreases with increasing the lag.	27
2.13	Interpolated empirical covariance between a base locations and other (99) grid locations in Delhi dataset. In the first plot, all the locations around the base location A has very low covariance with A. In the second plot, the locations at same distance from the base location G have different covariance w.r.t. G. . . .	27
2.14	One LCS unit co-located with a CAAQMS	28

2.15	Scatter plot for the CAAQMS and our low-cost mobile sensors. (Top) Colocated CAAQMS and our low-cost static sensors, (Bottom) CAAQMS and our low-cost mobile sensors passing nearby within 4km. We can observe that low-cost sensors show high $PM_{2.5}$ for relatively low $PM_{2.5}$ at CAAQMS.	28
2.16	Learn the calibration model using meteorological factors (Temp. and RH) over colocation <i>A</i> and test it over the two colocation CAAQMS at <i>B</i> and <i>C</i> . We observe good generalization of the calibration models from <i>A</i> to <i>B/C</i> for both static and mobile data. The number in the legend is the RMSE for respective algorithm.	29
2.17	Sorted mean $PM_{2.5}$ plot for different LCS after calibration. Some locations experience higher absolute PM due to hyper-local factors.	30
2.18	For Delhi region, CAAQMS sensors are in Black, the 4 grid locations for our Low-Cost Mobile Sensors are in Green. The traces in red/orange/yellow colours depict the trajectories covered by different buses having our low cost mobile sensors. Red colour depict high $PM_{2.5}$ whereas orange/yellow depict relatively lower $PM_{2.5}$. Also, thinner traces depict less number of samples (less bus travel) and bigger traces depict high number of samples (frequent bus travel).	31
2.19	For Delhi data, learn the calibration model using meteorological factors (Temp. and RH) over virtual colocation <i>G1</i> at ITO CAAQMS and evaluate over the other virtual colocations <i>G2</i> , <i>G3</i> and <i>G4</i> . Similar to the Kolkata calibration, we observe good generalization of the calibration models from <i>G1</i> to <i>G2/G3/G4</i> for the grid mobile data. The number in the legend is the RMSE for respective algorithm.	32
2.20	Graphsage architecture.	35
2.21	PM Data Splits. (a) $A \cup B$ forms the whole dataset for the <i>T</i> train days, $C \cup P$ forms the whole dataset for the test day. Spatial locations of <i>C</i> or <i>P</i> are independent of spatial locations of <i>A</i> or <i>B</i> . (b) Set of <i>A</i> and <i>B</i> spatial locations for 3 PM to 4:30 PM on Dec 15, 2020 from all bus-routes.	37

2.22	Interpolation RMSE. Training days' data is used by ML model in (a) and not used in (b). The Calib in X-axis labels denote experiments with the calibrated data. For Kolkata, (S) denotes static LCS data and both Static+Mobile data otherwise.	38
2.23	Errors for different $PM_{2.5}$ levels (at intervals of 10) for RF algorithm, with the number of test samples. Modeling shows high errors at high $PM_{2.5}$, making Delhi dataset hard to model due to high $PM_{2.5}$ levels.	39
2.24	Forecasting RMSE. (a) Normalization is done across all days. (b) Comparison of normalization across all days (T) vs normalization over each day. (c) Run-time (in seconds) for different forecasting algorithms for calibrated Delhi and Kolkata datasets.	41
3.1	High Resolution Pollution Maps for the three seasons (above) and three days in Winter (below). We find that the pollution patterns are different in the three seasons, also being significantly different even in the subsequent weeks. These fine-grained pollution maps further substantiate the profound impact of regional and seasonal factors (green cover, primary cooking methodology, industry vs. residential districts, proximity to roads, wind speed, humidity, etc.).	46
3.2	The exact same patterns are seen across 7 different static LCS locations on different days in Spring season. Similar patterns for Winter season are shown in Figure 3.3.	47
3.3	The exact same patterns are seen across multiple different static (Left) and mobile (Right) low-cost sensors on different days in Winter season. This points the presence of some regional factor like rain affecting $PM_{2.5}$ across the city.	47
3.4	Hyperlocal $PM_{2.5}$ observations for S03 and S18 in the morning. Peak $PM_{2.5}$ is the maximum hourly PM.	48
3.5	RL based framework RLSELECT. Blue are the sensor nodes from $\mathcal{S}_1$, and Green are from $\mathcal{S}_2$. For all nodes from $\mathcal{S}_2$, this algorithm gives recommendation probabilities, allowing b recommendations in total.	52

3.6	RMSE with recommendation algorithms for different temporal feature choices, lower is better. Using only hour of the day leads to high RMSE due to variance in the data over different days and seasons. Marking each hour separately leads to the best RMSE performance, tackling the high variance.	55
3.7	Interpolation RMSE in Delhi and Canada.	59
3.8	Recommendations for different algorithms.	60
3.9	RMSE performance for (a) precipitation dataset and (b) forecasting prediction model.	61
4.1	Google Maps Location of the intersection and installed cameras in New Delhi. Approach 1 has cameras 1-2, approach 2 has cameras 3-4, approach 3 has cameras 5-6.	65
4.2	Traffic Data Availability for the six cameras from Sep-Dec 2020, each colour denoting the data coming from separate camera.	68
4.3	Background Subtraction for Queue and Stop densities.	69
4.4	Good Yolo labeling (Left), Bad Yolo labeling (Middle) and Good traffic density (queue density and dynamic density) (Right). Green/red vertical lines in traffic density indicates the event of green/red signal.	70
4.5	Histogram of Queue and Stop densities for the 6 cameras for the 40 days for total 2,160,040 samples.	72
4.6	Traffic Patterns observed at an intersection in developing country.	73
4.7	Allowed phases at intersections	76
4.8	DRL architecture and actions.	77
4.9	Domain knowledge based optimizations	79
4.10	DRL states from four signal phases	80
4.11	Heterogeneous intersection, with both two-laned and three-laned approaches . .	80
4.12	Training Convergence over RL models. For time taken per episode, PL takes N seconds and FL-L variant takes 0.71N seconds.	83

4.13	Evaluation metrics for various algorithms on different Switch Policy and Dataset	83
4.14	(Left) Allowed phases at intersections (Right) Performance over different phase schemes, numbers at bottom of bars denote throughput, darker bars denote travel time and lighter bars (at the top) denote total time.	85
4.15	Performance over scaled road lengths, numbers at bottom of bars denote throughput, darker bars denote travel time and lighter bars (at the top) denote total time.	85
4.16	Blind and Explored learning methods.	87
4.17	Convergence of Teaching Strategies, Dotted Lines denote Throughput, and Solid Lines denote Total Time.	87
4.18	Transferability/Adaptability of the methods.	89
4.19	MAML based Enhanced Adaptability.	90
4.20	DRL training and LUT structure	92
4.21	Goodness metrics based DRL training	93
4.22	Goodness metrics based DRL selection	93
4.23	Density vs action	95
4.24	Developing Region Traffic Density Estimation	99