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DETERMINING TRANSPORTATION INDUSTRIAL METRICS USING RANDOM PROCESS THEORY AND ANALYTICAL HIERARCHY PROCESS

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ABSTRACT

Transportation is one of the inevitable and in-disposable shipment facilities for the huge number of people in our world. In our day to day life plenty number of segmented people use their own conveyance for any type of shipment. In our study we used to find which type of shipment is economical and also convenient for the lower and middle class people. For that here we identified three of mass transportation method much be appreciated for the people in huge mass. The three types of public transportation means are Metrorail, Monorail and Bus Rapid Transport System (BRTS). In this paper we took 19 cities into account for the above said transportation. Our aim is to find which mode of transportation is economical and viable in the cities for the people, to obtain a conclusion we identified ten attributes for measuring the mode of public transportation. From the plenty number of websites data has been taken for the respective attributes for 19 cities the semantic table and the tuples available are vital for our observation and identification. Here we employed two methodologies in terms with the Random Process Theory (RTP) and Analytical Hierarchy Process (AHP) which is ever been used in this segment and this is the first time we proposed such a type of a phenomenal methodology for the past one and half decades in this field of public transportation.

Keywords: analytical hierarchy process (AHP), transportation, random process theory (RTP), Markov Chain (MC).

1. INTRODUCTION

Shipment is a vital one in the existing universe. Transportation plays a major role for shipping the commodity and the people from one location to another based on demand management in Different Transportation Demand Management (TDM) policies integration is done [1]. Huge number of people on or below the poverty line needs some public transportation that reduces the cost and increases their convenience all the way. In India space and population are the essential one to decide, which kind of transportation vehicle is much be needed. Sustainability of the transportation speaks in the paper about the credentials of DRT services using Mode share of these DRT services against car or bus travel, was simulated from mixed logit models within a panel data modelling framework, institutional barriers for new DRT schemes need to be overcome in order to develop a sustainable local public transport system [2].

Space, speed, time, cost and convenience are the major factors to be considered for transportation. Resolving such a problem helps the people to make their journey comfortable citied in Users should be empowered to influence the service, which will give flexibility to the systemand foster bottom-up development and advanced public transport solutions [3]. For that, the major transportations are available like train, bus and monorail. Among the above said five, space role is inevitable. Year by year population and need for the transport is going in direct proportion. In our study we would like to find which one satisfies the above all in an optimum way. For that in this segment, for the past one and half decades, no one applied this Random Process Theory (RTP) in too 'Markov chain' and Analytical Hierarchy Process (AHP) methodologies in this segment. For optimum cost and convenience we used feature selection method to reduce the dimension of our data set by pruning out some less needed attributes among 10 attributes. Dataset was semantically formulated from different websites and incorporated for 19 metro cities in the above mentioned dataset. This feature selection helps us to reduce the computational time and the result will be converged in a faster manner.

In the following sections we can discuss about relative work, proposed methodologies, architectural diagram, result and discussions, conclusions and references

RELATED WORK

Evaluation of a transportation system using dominance-based rough set theory (DRST) [11]. The paper proposed and demonstrated that candidate sets can be used In order to cover the shortage of the classical association rules optimized Elcat algorithm it is suitable for the data mining of transport management information association rules [1 Route relationship matrix method is applied to find the routes and provide traffic solutions [13]. The application of data mining and available data mining tool in transportation engineering ector [14]. Statistical and data mining techniques to clusters of

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individuals by daily activity patterns for urban transportation [15] A centrality index and attractiveness indices for detecting the urban spatial structure, it represents a way of quantitative urban analysis and explicit urban change identification [16] A feature of Fixed Stop Rate (FSR) is used to distinguish the different types of transport modes. A frequency-based regular route mining algorithm is used to find the mined regular routes and transport modes on which a grid-based route table is constructed [19]. Passenger data is collected using smart cards and Spatial-temporal mining is applied tom calculate the demand [20]. An approach for context-aware public displays to improve personalized information access according to a user's language, location, time or other individual preferences using data mining [21]. Touching Transport, an application that allows a diverse group of users to visually explore public transit data on a multi-touch tabletop. It provides multiple perspectives of the data and consists of three visualization modes conveying tempo-spatial patterns as map, time-series, and arc view [22]. Mining characteristic patterns of the transport routines of urban bus riders for the design of travel information system [23]. A dynamic data-driven approach to improve the model for promoting an extended use of the simulation model the simulation study uses real data streams for automatic model calibration at run-time [17]. Discrete wavelet transform is adopted to cluster traffic flow series then Self-Organizing Map (SOM) algorithm is then used to cluster road links into groups [18]. Data Mining based Traffic Direction Control Algorithm (DMTDCA) is proposed to adjust the traffic direction of Direction-Changeable Lanes (DCLs) in the tunnel automatically [24]. Extraction existing traffic information from heterogeneous traffic information systems using k-multimodal shortest path algorithm [25].

COMPARISON OF THE STATE OF THE ART LITERATURE

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Table-1. Literature analysis.

S. No.	Authors	Proposed methodologies	Purpose	Quality of service
1	Tim jryley *et al* [2014]	Market identification mining	Contribution of Demand Responsive Transport	Sustainability
2	M. Habibian *et al* [2011]	Information theoretic interpretation	Transportation Demand Management	Integration
3	Gregorio gecchele *et al* [2011]	Cluster analysis method	Estimation of Annual Average Daily Traffic	Robustness
4	Mingjunliu *et al* [2012]	Elastic analysis method	Analysis Of Traffic Status	Sustainability
5	Francesco filippy *et al* [2012]	Neuro fuzzy methodology	Empower User and Improve Public Transport Service	Integration
6	Enniocascetta *et al* [2012]	Quantitative methodology	Planning and Designing of Urban Transport	Cost-effective
7	P.phanikumir *et al* [2013]	-	Effectiveness in Performance Of the Multimodal Transportation	Efficiency
8	Piotrsaiwicki *et al* [2014]	Dominance based rough set theory	Assignment of The Appropriate Transportation	Safety
9	XiaofengZheng *et al* [2014]	Pruning Éclat algorithm	Road Transportation Management Information System	performance
10	Yin kui-ying *et al* [2012]	Public traffic Mathematical mining	Optimize the Travel Time	Short time Travel
11	SasankReaddy *et al* [2011]	Discrete hidden Markov model	Transportation mode analysis	Flexibility
12	Sudhir Kumar Brai *et al* [2003]	Decision tree	Analyze vehicle Crash data	Safety
13	Shan Jiang *et al*	K-means clustering	Design of Suitable Transportation method	-
14	Chen Zhong *et al*	Spatial data mining		-
15	Wen He *et al*	Route processing Mining	Analyze Traffic Congestion	Mobility, effective
16	Lijun Sun *et al*	-	Personalized Information access	Visualization
17	Diana Lemme *et al*	-	Conveying Tempo-spatial Patterns	Robustness
18	Till Nagel *et al*	-	Transportation applications	Energy and Cost Efficiency
19	Stefan Foell *et al* [2014]	Prediction mining		
20	Yilin Huang *et al*	Simulation Methodology	Real Time Rail Monitoring Systems	Sustainability
21	Edmond Chin-Ping Chang *et al* [2004]	-	Monitoring Traffic	
22	Yudong Cheng *et al* [2007]	Discrete wavelet transform	Traffic Flow Prediction	Flexible Analysis
23	Xiaoyan Gong *et al* [2008]	-	Traffic tide phenomenon	Efficiency
24	Yin wang *et al*	Principle component analysis	Features of Temporal and Spatial Relationship	performance
25	Ciyun Lin *et al* [2009]	k-multimodal shortest path algorithm	Information System and Platform	-

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EMPIRICAL ARCHITECTURE

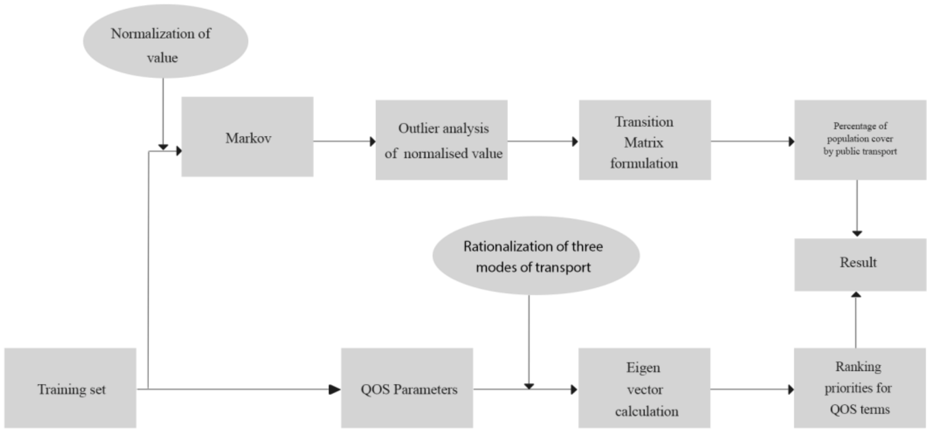

Figure-1. Proposed Architecture for the optimal selection of public transportation.

PROPOSED METHODOLOGY

A) Markov process

It is a simple stochastic process in which the distribution of future states depends only on the present state and not on how it arrived in the present state the Markov The transportation modes identified using a decision tree followed by a first-order discrete Hidden Markov Model and achieves an accuracy level of 93.6% when tested on a dataset [4]. Many systems in real world have the property that given current state, the past states have no influence on the upcoming state. This property is known as Markov Property. In this paper we are applying the Markov Chain process to find out the best suitable mode of public transport in metropolitan cities of India. So we have considered Population, Area of coverage, Present Ridership and Total Area as our parameters.

Table-2. Analysis of data.

City	Population	Area (sq.km)	Present ridership (observed)	Future ridership (expected)	Distance (km)
Chennai	4343654	426	72192	76800	45
Lucknow	4486639	485	131768	140179	28.14
Jaipur	3073350	249	49105	52240	9.2
Surat	2117990	142	72800	80000	25.6
Nasik	1607824	360	30403	33410	30
Nagpur	2405421	228	330330	363000	38.2
Mumbai	12478447	603	445000	500000	11.4
Hyderabad	6809970	650	53580	57000	73
Pune	5049968	710	188921	207606	82
Kanpur	3767031	605	31850	35000	84
Indore	1960631	530	62300	70000	32
Delhi	25000000	1484	2683800	2700000	192.7
Bangalore	10178146	741	37957	40380	42.3
Bhopal	2368145	697.2	200200	220000	78
Patna	5772804	3202	29760	32000	60
Rajkot	1286995	170	15980	17000	63
Coimbatore	2136916	246.8	54245	57707	20
Kozhikode	2030519	128	4700	5000	14.5

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Table-3. Markov data.

City	Population	Area	Ridership	Public transport coverage
Chennai	43.5	43.6	0.729	0.76
	82337.04	8233	1376.7	1376.72
Lucknow	45.14	45	1.38	1.316
	91465.5	91180.5	2658	2649.8
Jaipur	30.7	31	0.49	0.5
	28945.93	28949.9	460.63	4606.69
Surat	21	21.02	0.73	0.76
	9265.26	9274.194	321.4189	3217.7306
Nasik	16.07	16.09	0.3	0.32
	4154.49	4160.02	78.99	79.1
Nagpur	24.08	25	3.35	3.36
	13945.57	129.43	1941.7278	18.06
Mumbai	124.804	124.792	4.454	4.452
	1943870.25	1943683.24	69480.53	69473.81
Bangalore	102	103	0.38	0.4
	1061342.67	1061725.06	3969.28	3970.71
Bhopal	24.06	24.07	2.07	2.08
	15086.88	465.53	1298.3	40.06
Patna	3.8	3.6	0.58	0.042
	195213.96	12117.78	0.2	0.01
Rajkot	13	13.06	0.15	0.38
	2197.97	2208.84	26.64	26.86
Coimbatore	21	21.01	0.54	0.55
	9266.29	9270.76	240.5	240.61
Kozhikode	20	21	0.041	0.055
	8000.659	8005.41	16.002	16.01
Hyderabad	68.24	68.1	0.69	0.53
	318912	3112	3218	31.32
Pune	50.51	50	1.92	1.97
	133671.73	1939.56	5060.52	73.46
Kanpur	3706	37.75	0.318	0.42
	53807	898	456	7.6
Indore	49.22	49.33	0.47	0.48
	11942	13732	1140	131.1
Delhi	250.11	250.13	2.91	2.94
	15802463	64378	183880	749

B) Analytical hierarchy process

Analytic Hierarchy Process is one of the widely used methods for multi-criteria decision making and model-based clustering methods give slightly better results [5]. It allows the use of both qualitative and quantitative criteria into evaluation. It develops a hierarchy of decision parameters and defines the alternative courses of action. In this process we would determine the relative weights of the decision parameters as well as determine the relative rankings (priority) of the alternatives for the Deployment of the components of the Intelligent Transportation Infrastructure (ITI) [6].

C) Ranking of parameters and alternatives

In this pairwise comparisons are made with the grades ranging from 0 to 1. In our work we have taken three modes of public transportation (i.e.) METRO, MONORAIL, BRTS and nine parameters of Quality of Service (QOS) in order to decide which mode of public transport is best suitable for mass transit of people as it was done in the detailed implementations of public transport priority (PTP) in Beijing city and analyzes the traffic operation status after the strategy [7]. Parameters taken into consideration include Reliability, Robustness, Customization, Security, Performance, Scalability, Usability, Cost-effectiveness and Time of Travel.

Table-4. Analytical hierarchy process.

Mode of transport	Reliability	Robustness	Customization	Security	Performance	Scalability	Usability	Cost effectiveness	Time of travel	E1
Metro	0.12	0.06	0.12	0.12	0.06	0.06	0.25	0.12	0.06	1.0262
BRTS	0.06	0.12	0.12	0.06	0.06	0.12	0.06	0.12	0.25	1.0015
Mono rail	0.06	0.12	0.06	0.12	0.25	0	0.06	0.25	0.12	0.09718

D) Standard deviation and variance calculation

Variance measures how far a set of numbers binge out. A variance with the value zero indicates that all the values are identical. Variance is always non negative number. The standard deviation (SD) (represented by the Greek letter sigma, σ) is a measure that is used to enumerate the amount of variation or dispersion of a set of data values. In our paper we use variance and standard deviation on the result of Markov and AHP to find out the best mode of transportation and significant features of the traffic network by using variant features [8].

Parameters that are covered in our paper include the role of Public Engagement in planning and designing transportation systems, describing its interactions with other more formal phases of decision-making [9]. The calculations include Percentage of population using public transport and Percentage of area covered by public transport

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Table-5. Standard deviation and variance.

Cities	% of population	% of area coverage	Normalized value (X)	$(X-\overline{X})^2$
Chennai	0.0168	0.0174		
	0.0167	0.1672	0.1839	0.009204488
Lucknow	0.0306	0.0292		
	0.0291	0.0291	0.0581	0.000892744
Jaipur	0.0160	0.0161		
	0.0159	0.1591	0.1750	0.007575918
Surat	0.0348	0.0362		
	0.0347	0.3470	0.3816	0.086227998
Nasik	0.0187	0.0199		
	0.0190	0.0190	0.0380	0.002497251
Nagpur	0.1391	0.1344		
	0.1392	0.1395	0.2788	0.036393596
Mumbai	0.0357	0.0357		
	0.0357	0.0357	0.0715	0.000272686
Bangalore	0.0037	0.0039		
	0.0037	0.0037	0.0075	0.006483513
Bhopal	0.0860	0.0864		
	0.0861	0.0861	0.1721	0.007074048
Patna	0.1526	0.0117		
	0.0000	0.0000	0.0000	0.007743674
Rajkot	0.0115	0.0291		
	0.0121	0.0122	0.0243	0.004060174
Coimbatore	0.0257	0.0262		
	0.0260	0.0260	0.0519	0.001302637
Kozhikode	0.0021	0.0026		
	0.0020	0.0020	0.0040	0.007056003
Hyderabad	0.0101	0.0078		
	0.0101	0.0101	0.0202	0.004602968
Pune	0.0380	0.0394		
	0.0379	0.0379	0.0757	0.000150494
Kanpur	0.0001	0.0111		
	0.0085	0.0085	0.0169	0.00504981
Indore	0.0095	0.0097		
	0.0955	0.0095	0.1050	0.000289287
Delhi	0.0116	0.0118		
	0.0116	0.0116	0.0233	0.004189899
		total sum	1.6879	0.19106719
		average	0.088837573	

Legend: RED-indicates out of bound value, GREEN-indicates value within range

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Steps involved

Find the normalized values (X) for all cities

Compute ($\bar{X}$) = average of X =1.6879/18, Hence it gives the value 0.088837573.

Calculate Variance=Sum of $(X-\overline{X})^2/18$, it gives 0.0106.

-Calculate Standard Deviation

Standard deviation: =√ (variance) =0.1030.

-Calculate Limits (Outlier Analysis), Lower limit= 0.0888-0.1030= -0.0142, Upper limit=0.0888+0.1030= 0.1918.

METHOD FOR FINDING WHICH MODE OF PUBLIC TRANSPORT IS BEST

Table-6. Mode of Transportation.

Mode of Transport	Chennai	Lucknow	Jaipur	Surat	Nasik	Nagpur	Mumbai	Hyderabad	Pune
Monorail	no	no	no	no	no	no	yes	no	p
BRTS	p	no	yes	no	no	no	p	p	yes
Metro	u	yes	u	u	p	u	yes	p	p

Mode of Transport	Kanpur	Indore	Delhi	Bangalore	Bhopal	Patna	Rajkot	Coimbatore	Kozhikode
Monorail	p	p	no	p	no	p	no	p	p
BRTS	no	yes	yes	yes	p	p	no	no	no
Metro	p	p	yes	p	p	no	yes	p	no

Legend: p->indicates the transportation under planning, u->indicates the transportation under construction

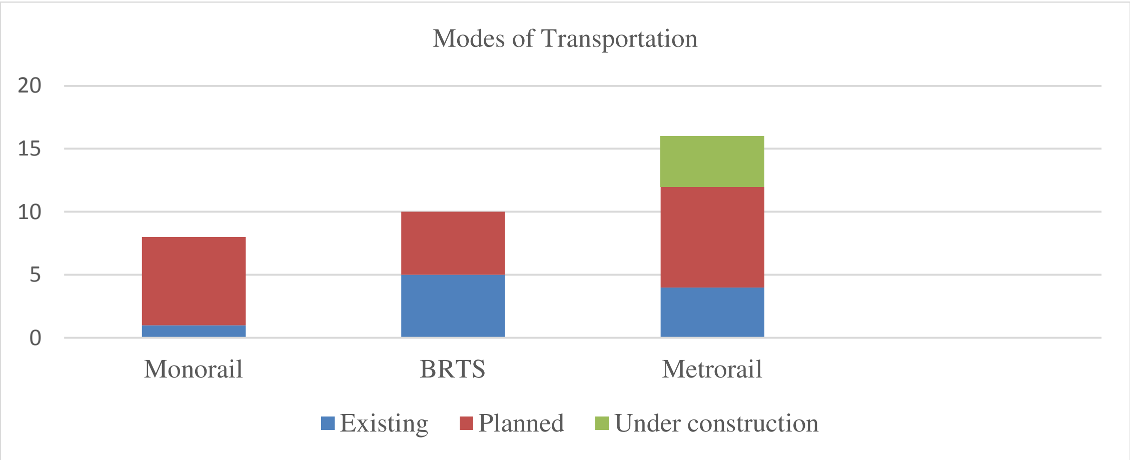

Figure-2. Mode of Transportation.

The chart-1 represents the mode of transportation existing, planned, under construction in the metro cities of India.

After doing outlier analysis for the above cities out of 18 cities there were only 14 cities that are within the limits.

Table-7. Analysis of Transportation.

	No. of cities using monorail	No. of cities using metro rail	No. of cities using BRTS
	5	13	8
Ratio	(5/26)	(13/26)	(8/26)

Mode of Transport having the highest ratio will have highest percentage of usage. In our analysis we found that metro train is the best mode of transport.

RESULT AND DISCUSSIONS

In this paper the Analysis data is taken and normalized for applying Markov methodology. The ridership and the public transport coverage were 2.91 and 2.94 for Delhi (Table-3). On applying Markov process we were able to predict the future ridership and the public transport coverage to be 183880 and 749. The AHP methodology has been applied on QOS parameters like reliability, robustness, security etc. to find which mode of public transportation satisfies the maximum QOS parameters. In our paper we got metro satisfies almost all parameters with the highest eigenvector value of 1.0262 (Table-4). In the analysis of Transportation we found in 13 cities where Metro Rail was best suitable. The ratio of acceptance was found to be high for Metro Rail Transportation Evaluate performance of multimodal transportation system (MMTS), where metro became main mode in routine public transport trips. The present bus services, metro rail and IRBT (Integrated rail-cum-Bus Transit) can carry more passengers [10].

CONCLUSIONS

For determining which mode of transport is the best in all metropolitan cities we have chosen three mass modes of transport (i.e.) BRTS, Metro Rail, Mono Rail. In this paper we have applied two methodologies namely Markov Chain Process and Analytical Hierarchy Process (AHP). Based on Total Ridership and Total Area Covered by transport modes we were able judge which mode of transport is the best. Analysis is done based on the Percentage of population using the Public Transport. By applying Markov process we were able to predict the percentage of ridership value and percentage of area coverage by these modes over a period T. After this process we have applied Outlier Analysis method in order to state which cities lies within bound (i.e. the cities which cover major population and area). Ongoing through this result we came to a conclusion that Metro is the best mode of public transport available in almost all the metropolitan cities. Another methodology (i.e. AHP) that we had applied states which mode is the best based upon the QOS terms. It is noted that Metro Rail satisfies almost all QOS terms, so in both the methodologies like Markov Chain Process and Analytical Hierarchy Process Metro Rail lies high.

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