

Demand Prediction on Bike Sharing Data Using Regression Analysis Approach

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Abstract: In order to forecast the need for bike-sharing services, this paper suggests a rule-based regression model. Commuters and tourists alike are taking advantage of public bike sharing programs because of the convenience and low carbon footprint they provide. Used information from the UCI Machine Learning Repository. Repeated cross-validation was used to fine-tune the hyper-parameters of five statistical models. Conditional Inference Tree, K-Nearest Neighbor Analysis, Regularized Random Forest, Classification and Regression Trees, and CUBIST. The predictive accuracy of the regression models was measured by calculating the Root Mean Squared Error, R-Squared, Mean Absolute Error, and Coefficient. For both the Seoul Bike and Capital Bikeshare programs, the rule-based model CUBIST was able to account for 95 and 89% of the Variance (R^2), respectively. All models built from the two datasets using WEKA v3.8.6, and are used a variable significance analysis to establish which variables were most crucial. The most important factors in determining the hourly demand for bike rentals are the weather and the time of day.

Keywords: *demand prediction, regression analysis, Machine learning, DSS, WEKA.*

I. INTRODUCTION

Bike sharing is an excellent alternative to driving . With a shared bike, you may avoid parking and traffic. You can pick the perfect shared bike for your needs. Copenhagen, Amsterdam, and San Francisco have popular bike-sharing schemes [1].

What's bike sharing? You'll get a bike when you join a bike-sharing program. Then register your bike with the program. This allows the application to track your bike and ensure its returned [2].

Safe? Yes, bike sharing is safe. Each bike has a GPS system to ensure it's returned to the docking station. The bike sharing systems also undertake frequent safety audits [4].

Bike sharing lets riders share small electric vehicles. Why? You can use a shared bike while someone else is riding it, unlike an elevator [5].

Why? You get a bike from a docking station. Next, scan the bike's QR code to unlock it. When you're done, let go of the bike and it will automatically return to the docking station. Bikes can be leased for a day or more. You can leave the bike at the station or return it to the owner [3].



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What's unique? Bike sharing is cheaper and more environmentally friendly than cars or buses. What's the use? Bike sharing has several uses. 1. It's a city bus. Bike sharing is fast, convenient, and economical for short city excursions. 2. It lets you explore the city. Bike sharing is a fast and economical method to explore new neighborhoods. 3. It speeds up travel. Bike sharing is a fast, economical way to get about. It saves money. Bike sharing is a cheap, fast way to get about. 5. Meet new people. Bike sharing is a fast, economical method to meet new people [6].

A research indicated that most Philadelphians bike to work. In Beijing, bike sharing is utilized for travelling, shopping, and going to destinations not accessible by public transit. Toronto commuters and tourists use bike sharing [1, 7].

Price affects bike sharing utilization. Users may not be able to afford the program if the bikes are too expensive. If bikes are too cheap, the program may lose money [8].

Bike placement affects bike sharing utilization. Inaccessible bikes may prevent consumers from using the service. Finally, user location affects bike sharing. If users are in a hard-to-reach area, the program may not work [9].

Bike-sharing is popular. Bike-sharing users borrow and return bikes. Our data shows 2 million Americans use bike-sharing. People spend an hour a day on bike sharing, boosting demand. Bike sharing may become widespread in the U.S. Bike sharing decreases traffic, improves health, and protects the environment. Bike-sharing has downsides. Bike-sharing may be popular. Accidents can result. Costly bike-sharing programs. Poor people may struggle [5].

ML automates learning. Computers can learn through machine learning. ML creates data-learning and forecasting algorithms. ML produces data-learning algorithms. Computers learn from experience using machine learning. [10].

ML builds prediction models. Data-driven predictive modelling forecasts future events. Model predictions are made. Data and algorithms power machine learning. Data aids AI. Machine learning algorithms are supervised and unsupervised. Training data with output labels uses supervised learning. Unsupervised learning methods are utilized without labels. Machine learning enables classification, regression, and prediction [11].

Machine-learning classifiers predict object class. A trained classifier predicts new item classes. Classifiers include DTs, SVMs, and NNs. Machine-learning classifiers label data. Face recognition, spam detection, and medical diagnosis use classifiers [12].

ML regression predicts real output. Trained regression can predict new item value [13].

Regression models input-output. Regression uses numeric input and output variables. Regression models input-output by calculating a prediction function. Regression accurately predicts input results. Regression predicts revenue from consumer data. Regression accurately predicts input results. [14].

Using a linear function, linear regression predicts real output. New item values can be predicted using linear regression. Using a logistic function, logistic regression predicts binary output. A dataset-trained logistic regression can predict new object values. [15].

Machine learning algorithms anticipate time-series values. Fresh things' future value can be predicted. Forecasts are generated by extrapolating prior time-series values and using a model. Predictions help decide on future events and forecast time-series values. Company, stock, and market success can be predicted [16].

This research analyses bike sharing demand in a city and predicts usage. We'll utilize machine learning to estimate when people will use bike sharing..

II. LITERATURE REVIEW

Due to ageing infrastructure, system problems, and man-made or natural disasters, the metro often has planned service interruptions [17]. Commonly, parallel replacement buses cross disrupted lines [18]. This method's poor capacity is limited by metro lines and surface traffic. Transit agencies need multimodal interchanges.

Long-term metro maintenance closures are often notified in advance, unlike daylong strikes or emergencies. Well-educated travelers can alter their transit. These changes may reflect passenger adaptations to rapid shifts. They show that a large and swift transformation in travel policy and travel patterns is possible [19]. Long-term disruptions in public transportation give an opportunity to build, through trial, a better approach to transportation policy [17].

In the last 20 years, bike sharing has expanded globally. Three factors have contributed to the rapid growth of bike sharing programs worldwide. The government is becoming increasingly alert to the unexpected consequences of growing auto use, such as increased pollution and traffic congestion [20]. Second, as a crucial aspect of future "smart cities," bike sharing programs will offer more flexibility than traditional public transit and contribute to positive social and environmental results [20-22]. According to [23], bike sharing can solve the built and social environment's first- and last-mile transit problems. First and last leg public transit is usually limited [24]. Bike sharing is a potential viable solution in the event of transportation interruptions, especially scheduled system closures [19]. Integrated bus, light rail, and bike-sharing systems can cut transit times. This can promote a greener way of urban transportation [25, 26].

Most studies on public transit shutdown have not considered bike-sharing as an option [17, 27-30]. This is despite the fact that bike sharing might be used as a public transit alternative.

These [19, 31-33] are the only studies that have examined how public transportation disruptions affect bike sharing. During each strike phase, the number of daily bikes sharing rides and their duration increased significantly. We focus on planned transportation closures rather than strikes, which are distinct. Each surge lasts at least seven days, and maintenance only affects a fraction of a station's service area and surrounding area.

[31] We used a paired t-test simple linear regression model to evaluate how metro service disruptions affect bike sharing when single-trip fare (STF) and SafeTrack operations commence simultaneously. They didn't differentiate between continuous single-tracking (CST) and line segment closures (LSS).

The authors did not account for intentional disruptions in the regression model, which only considered the seven-day period before, during, and after each surge. Weekend trips and rainy-day observations weren't considered. [19] used an autoregressive Poisson model to examine the effects of three SafeTrack surges on bike sharing. 2, 4, and 10 surges. They did not account for the over dispersion of travels data, the impacts of various influential radii and pedalling distance on the demand for bike sharing in the case that public transportation was unavailable, nor did they consider precipitation.

The average temperature used in their model is not a good indicator of the nonlinear relationship between temperature and bike sharing usage.

A. Factors Affecting Bike-Sharing

1) Weather Condition

Weather and climate affect bicycle use and frequency. In addition to long-term seasonal affects, short-term weather fluctuations may affect trip creation. Weather and surroundings affect whether someone uses BSP. Weather affects bike-sharing. Temperature, precipitation, and relative humidity affect travel demand, as does wind speed [34-36].

2) Temperature and Precipitation

Well-studied bike-effect sharing on temperature. Rising temperatures boost bike-sharing demand. Above 30 degrees, bike-sharing demand jumps. High temperatures affect bike sharing in

paradoxical ways. Toronto's bike-sharing demand rises 30°C in hot weather. South Korea had 49 30°C days [37]. Travel dropped. [38] showed bike sharing demand is strongest between 30 and 35°C.

Weather affects various age groups' bike sharing demand. 12-16°C is safe for all ages, but 27-32°C is harmful. 21-27 °C reduces 16-27-year-olds' travel productivity [39].

Low temperatures were unnerving for bikers. Rainy and cold days reduce bike sharing demand. Rain reduces trip demand and restores it within three hours. Academics say bad weather reduces bike-sharing demand [40].

3) *Wind Speed, Humidity*

Weather includes wind, humidity, temperature, and precipitation. Bike-sharing is affected [41]. Temperature-humidity index, relative humidity, and wind speed hinder bike sharing [34]. An increase from 14.7°C to 15.8°C raises hourly volume by 4–5% [42]. The effect was less significant above 28 °C and 60% humidity. Wind and humidity hindered bike sharing in Washington [43]. Wind speed and humidity reduce trip generation, say several experts.

4) *The Seasons and Climate*

Weather influences bike sharing demand; therefore, models must account for these fluctuations. Annual bike sharing statistics and monthly analysis are needed to assess the seasonal impact on bike utilization [44, 45].

Winter is a slow season for Great Rides, Boulder B-Cycle, and Capital Bikeshare. US researchers used a questionnaire to learn why prospective passengers wanted to use BSP in the winter and variables affecting biking. "Bike idle time" rises when it rains or snows, reducing bike-sharing demand [43]. Most BSP stations in Montreal are closed from November to April. April bike sharing grew 32%-39% [42]. Winter cycling demand reduces considerably, according to Citybike Vienna [46]. In Switzerland, bicycle use has increased in all seasons except summer [47].

5) *Built Environment and Land Use Factors*

Cities are great for biking because of their high population, employment, and retail density. BSP stations near tourist sites, leisure zones, and transportation hubs will expand bike-sharing services. Several studies have shown that the built environment and land usage influence BSP use [48]. As described here, building and land use affect bike share.

6) *Built Environment*

Cities that encourage biking need a good infrastructure. In 43 U.S. cities with good cycling infrastructure, bicycle use increased. Separated bike lanes make cyclists safer [49, 50]. Uninterrupted, divided lanes assist adult riders, especially women [51, 52]. Segregated bike lanes boost cycling the most, per [52]. Expanding bike lanes inspires all cyclists, according to [53]. Non-members join bicycle facilities with BSP stations [54]. BSP and bike lanes are connected. Off-road is a solo bike ride [48]. A 500-meter station buffer influences trip creation. The sidewalk length affects transit hub access [55] but not BSP utilization [38].

After two-way cycling lanes were created in Portland's city Centre, cyclists and motorists felt safer [56]. Bicyclists should avoid bike-and-car traffic. 10-minute travel duration correlates most [57]. Bike-sharing fell along unmarked, high-traffic SoBi BSP routes. Consumers like isolated roads [58]. Users prefer stations near their destination, says another survey. Bicycle safety is affected by design, volume, and attitude [59]. Safe and enjoyable bicycling requires a "minimum bicycle infrastructure" [60].

Night cyclists must be safe. Streetlights have improved bike use and reduced crime [61]. Homicides in a 1.6-km station buffer lowered bike sharing use. Lack of bike parking and theft limit Dutch train station cycling [62]. Bike routes, secure parking, rentable bikes, docks, and racks ease station access [63].

7) *Land Use*

Land use affects bike-sharing demand. Slope affects bicycle use. Bikes are rented from above and left on a cycling slope below. Hillside BSP stations bother female commuters. Steep grades

increase riding effort and driving speeds. Above 4% gradient, bike-sharing declines [58]. Uphill grades limit bike sharing demand, claim Hood, Sall, Charlton, Jennings, Bordagaray, dell'Olio, Fonzone, and Ibeas. Chongqing, Guiyang, and Dalian have low bike share. BSP. Incentivizing uphill bike sharing demand. E-bikes can be rented in hilly areas. E-bikes picked up/dropped at hilly stations may boost bike sharing mobility. Mountain station e-bikes [64].

8) *Public Transportation Factors*

Public transit planning and land use integration reduce vehicle use and promote cycling. 30% of 5-km business journeys in bike-friendly Netherlands are by automobile [65]. BSPs are used in China to reduce vehicle use and promote cycling. The factors impacting consumers' bike-share decisions were studied with the idea that BSP may reduce passenger demand in the public transport network and increase transportation system flexibility [66, 67].

Most US and Canadian BSP users believe it enhances public transit. Tel Aviv BSP statistics revealed how bikes can replace public transit. Shorter trips are better by bus. Bus vs. bike: distance, time, comfort, and effort [85]. Bicycles may replace buses in congested cities due to short distances and bad weather. In Helsinki, researchers studied BSP's impact on transit trip times. BSP shaves 6 minutes off transit trips. Faster BSP stations are well-integrated [68].

9) *Station Level Impact Factors*

BSPs include smart bikes, parking, and rentals. All systems except free-floating BSPs require station-based bike rentals and a smart parking unit. The closest station should be used. Close stations maximize coverage and bike rentals [69-72].

10) *Socio-Demographic Impact Factors*

Understanding the BSP consumer profile entails identifying socio-demographic parameters [73]. Gender, age, education, money, and car ownership affect bike-sharing demand. Young, male, well-educated, working, and wealthy are typical BSP members [20, 67, 74].

52.8% of responders were male, and 65.6% had some education or a \$50,000+ salary [75]. The Melbourne BSP group in Australia reported that 76.6% of users are male, 16.9% are between 30 and 34, 43% make over \$104,000 a year, and 81.0% had a college degree or higher.

11) *Temporal Factors*

Travel production was studied using models, calendars, and time-based factors. Weekends, holidays, weather (temperature, humidity, precipitation, wind speed), and geographical data were analysed (residential, commercial, industrial, green, and university districts). Weekend and weekday bike rentals were similar, while morning rentals were lower.

Vacations decrease bike-sharing. School vacations don't affect BSP use since under-17s can't join. Mateo-Babiano, Bean, Corcoran, and Pojani [48] found CityCycle members prefer free short-term trips and convenient station returns. Weekend travel boosts BSP consumption in the afternoon and weekday travel at rush hour. Weekend demand doubled [76]. Saturdays are busy around parking lots. "Peak working hours" and short trips favour BSPs [77, 78].

Around 7 am and after work, bike sharing demand increased [70]. Morning cycling boosts bike-share commuting. BSP is for quick excursions. Vélouv BSP motorcycles hit 14.5 km/h around 6 a.m. weekdays. Short bike rides are usually shorter than automobile rides. 10 km/h on Sundays [78].

12) *Safety*

Safety may motivate cycling. Different groups view safety differently. Accident-prone countries may mandate helmets. Tourists may have problems renting helmets from BSPs [79].

Peak-hour BSP helmets may prevent head injuries and deaths. BSP riders are helmet-free. DC BSP members wore less helmets than private bikers. BIXI members wore less helmets [80]. D.C. CaBi users don't use helmets. Citi Bike riders in New York were monitored 44 hours a week. 85.3% of Citi Bike riders are helmetless [82]. Citi Bike members and regular riders wear helmets. Citi Bike riders wear helmets more in the morning. Weekend helmet use is lower. BIXI BSP

women rarely wear helmets [80]. In August-October 2011, 46% of 4,789 Montreal cyclists wore helmets. Most Montreal BSP women wear helmets. 73% of teens and young adults wear helmets. Helmets are popular [81].

Previous research on helmet regulations and bike-sharing demand is equivocal. Due to "unplanned" shorter journeys, bike-sharing demand was negatively correlated with helmet use. Australia's helmet law reduced BSP. BSP users lack helmets. BSPs decrease helmet use. Helmets may lower BSP accident injuries and boost demand [83].

III. METHODOLOGY

The data used must be kept confidential, but the results must be compared to other conventional machine learning methods to demonstrate the pros and cons of each. Paragraph discusses study's algorithms. No machine-learning algorithm is perfect [84]. Five prediction algorithms' performance were compared.

1) *CUBIST*

Cubist extends Quinlan's M5 model tree with rules. Tree leaves contain linear regression models [85].

2) *Random Forest*

Popular machine learning method that belongs to the supervised learning technique is Random Forest [86].

3) *Classification and Regression trees*

CART is a machine learning predictive algorithm. It explains how to forecast a target variable's values [87].

4) *K-nearest Neighbours (KNN)*

KNN is a non-parametric, supervised learning classifier that employs closeness to group data points [88].

5) *Conditional Inference tree*

Conditional Inference Trees are a form of non-parametric decision trees also known as unbiased recursive partitioning [89].

Figure 1 and Table 1 describes the workflow of the research and workflow description of the research.

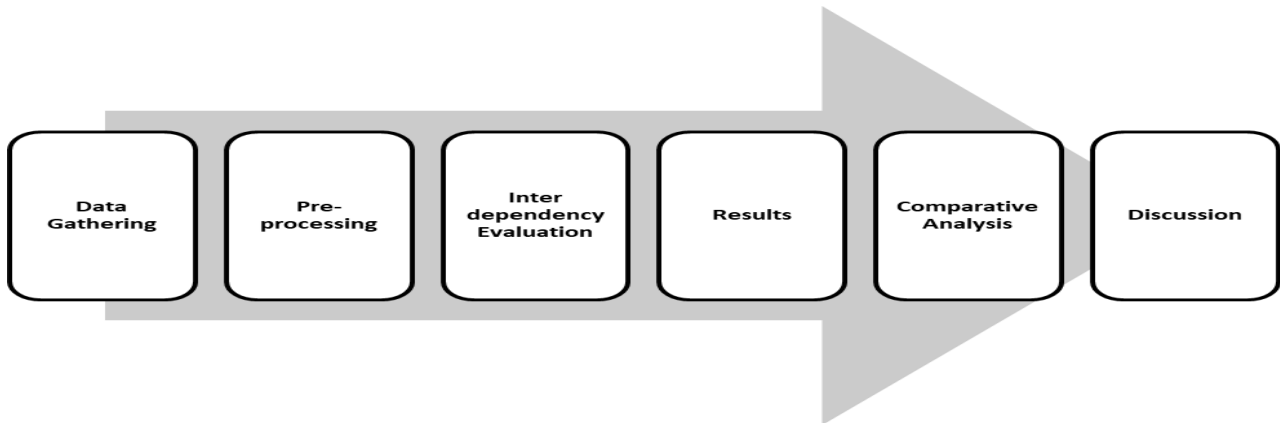


Fig. 1. Workflow of the Research

TABLE I. WORK FLOW DESCRIPTION OF THE RESEARCH

Index	Phase	Activities	Description	Technique
1	Data Gathering	Selection of Data Set	Data was downloaed from UCI with seventeen attributes containing numerical values.	Data Acquisition

2	Pre-processing	Data Cleaning, Outliers removal etc.	Missing values has been removed by expliting tuples. Attribues selection	Missing value detection Using Rankers Algorithm
3	Interdependency Evaluation	Corelations, Heat Map	Depandancy of each attribute was identified and visualized.	Ranker's Algorithm Phyton heat map visulization function
4	Results	Find the results applying different Algorithms	Results have been recorded by WEKA 3.8.6 using numerical data.	Regression analysis Descriptive evaluation
5	Comparative Analysis Compare Results			
6	Discussion			

IV. RESULTS AND DISCUSSION

Regression model accuracy is compared using a number of different metrics. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Correlation Coefficient (CV) and R2 are employed here as indices to measure performance.

In the following Table II results after applying five algorithms is given which shows that CUBIST / M5P's results are better although it took more time to build model.

TABLE II. 10 FOLD CROSS VALIDATION RESULTS WITH 17 ATTRIBUTES

Relation:	Hour				
Instances:	17379				
Attributes:	17				
Test mode:	10-fold cross-validation				
	Time in sec	RMSE	MAE	CV	R2
Random Frost	8.08	40.03	24.05	0.98	22.07
CIT / RePTree	0.38	44.31	27.72	0.97	24.43
CUBIST/M5P	10.14	0	0	1	0
KNN / IBK	0	75.43	51.02	0.91	41.58
CART/Random Tree	0.14	77.09	44.07	0.91	42.50

After removing attribute with negative values 14 attributes remains out of 17. Table III shows the results of algorithms applied on dataset with 14 attributes. It tells us that errors reduced with reduction of attributes. Still CUBIST/M5P show better results.

TABLE III. 10 FOLD CROSS VALIDATION RESULTS WITH 14 ATTRIBUTES

Relation:	Hour				
Instances:	17379				
Attributes:	14				
Test mode:	10-fold cross-validation				
	Time in sec	RMSE	MAE	CV	R2
Random Frost	7.19	39.13	23.43	0.98	21.57
CIT / RePTree	0.25	44.18	27.65	0.97	24.36
CUBIST/M5P	10.09	0	0	1	0
KNN / IBK	0	67.68	45.81	0.93	37.31
CART/Random Tree	0.14	74.25	40.71	0.92	40.93

Table IV depicts the final shortlisted attributes by applying Ranker's algorithm using CorrelationAttributeEval, ClassifierAttributeEval and ReliefFAttributeEval on WEKA version 3.8.6. so, 13 attributes are selected for the further processing including "cnt" attribute.

TABLE IV. FINAL SHORT LISTED ATTRIBUTES

Attributes	Description
registered	count of registered users
casual	count of casual users
temp	Normalized temperature in Celsius. The values are derived via (t-t_min)/(t_max-t_min), t_min=-8, t_max=+39 (only in hourly scale)

atemp	Normalized feeling temperature in Celsius. The values are derived via $(t-t_{min})/(t_{max}-t_{min})$, $t_{min}=-16$, $t_{max}=+50$ (only in hourly scale)
hr	hour (0 to 23)
instant	record index
yr	year (0: 2011, 1:2012)
season	season (1:winter, 2:spring, 3:summer, 4:fall)
mnth	month (1 to 12)
windspeed	Normalized wind speed. The values are divided to 67 (max)
workingday	if day is neither weekend nor holiday is 1, otherwise is 0.
weekday	day of the week

After removing one more element remain 13 attributes are tested. Table V shows the results of these. It is found the CUBIST/MSP still performs best.

TABLE V. 10 FOLD CROSS VALIDATION RESULTS WITH 13 SHORT LISTED ATTRIBUTES

Relation:	Hour				
Instances:	17379				
Attributes:	13				
Test mode:	10-fold cross-validation				
	Time in sec	RMSE	MAE	CV	R2
Random Frost	3.17	6.41	3.67	1.00	3.53
CIT / RePTree	0.06	7.21	4.97	1.00	3.97
CUBIST/MSP	0.27	0	0	1	0
KNN / IBK	0.01	40.12	28.81	0.98	22.12
CART/Random Tree	0.06	20.37	11.23	0.99	11.23

Fig. 2, Fig. 3 and fig. 4 depicts the visual representation of Table II , III and IV respectively.

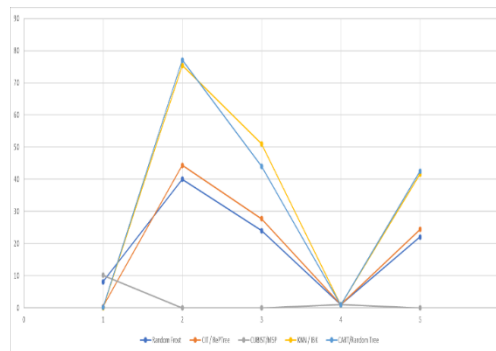


Fig. 2. Visualization of Table II

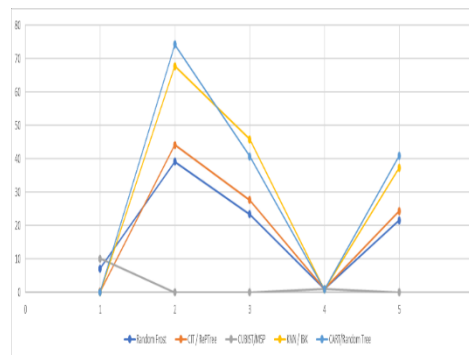


Fig. 3. Visualization of Table III

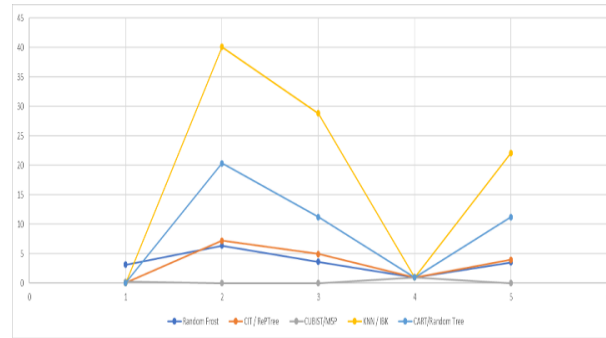


Fig. 4. Visualization of Table V

V. COMPARATIVE ANALYSIS

Table VI and fig. 5 shows the comparative results of all algorithms. It is found that CUBIST / M5P perform better than others although time to build model is more than others. It presents a comparison of the results obtained from using various algorithms. Upon examination, CUBIST and M5P demonstrate superior performance in comparison to the other algorithms tested. However, it should also be noted that the time required to construct the models using CUBIST and M5P is longer than the time required for the other algorithms.

TABLE VI. COMPARISON OF RESULTS

Relation:	Hour														
	17379					17379					17379				
Instances:	17					14					13				
Attributes:	17					14					13				
Test mode:	10-fold cross-validation					10-fold cross-validation					10-fold cross-validation				
	Time in sec	RMSE	MAE	CV	R2	Time in sec	RMSE	MAE	CV	R2	Time in sec	RMSE	MAE	CV	R2
Random Frost	8.08	40	24.1	0.98	22.1	7.19	39.1	23.4	0.98	21.6	3.17	6.41	3.67	1	3.53
CIT / RePTree	0.38	44.3	27.7	0.97	24.4	0.25	44.2	27.7	0.97	24.4	0.06	7.21	4.97	1	3.97
CUBIST/M5P	10.1	0	0	1	0	10.1	0	0	1	0	0.27	0	0	1	0
KNN / IBK	0	75.4	51	0.91	41.6	0	67.7	45.8	0.93	37.3	0.01	40.1	28.8	0.98	22.1
CART/Random Tree	0.14	77.1	44.1	0.91	42.5	0.14	74.3	40.7	0.92	40.9	0.06	20.4	11.2	0.99	11.2

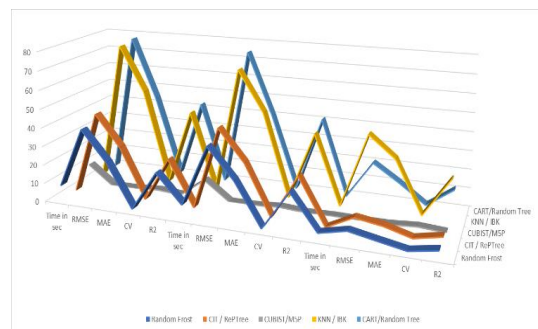


Fig. 5. Visualization of Table VI

VI. CONCLUSION

This research estimated bike-sharing demand using Bike dataset. CUBIST outperforms RRF, CART, KNN, and CIT in R2, RMSE, MAE, and CV. CUBIST can predict bike-share demand. Analyzing variable importance revealed hidden links. In all models, temperature or hour best predicted bike rental demand. This study found many links. This increases knowledge. It helps model hourly bike rental demand. CUBIST improves learning algorithms using rule-based learning. This study compares CUBIST to RRF, CART, KNN, and CIT to show its superiority in hourly rental bike demand forecasting. These results help academics predict hourly bike rental demand and expand empirically-based algorithms. Future research will predict seasonal bike rental demand district-wide.

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