JTS Jurnal Teknik dan Science

JTS Vol 4 No. 3 October 2025 | ISSN: 2828-7002 (Print), ISSN: 2828-6871 (online), Page 28-38

Adi Soemarmo Airport Train Demand Modelling Based on Google Cloud Big Data

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Article History
Received : 15-08-2025
Revised : 20-08-2025
Accepted : 19-10-2025
Published : 27-10-2025

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Cite This Article:
Purnomo, M. T., Indriastuti, A. K., Basuki, K. H., Kusuma, D. T., & Aghna, R. I. (2025). Adi Soemarmo Airport Train Demand Modelling Based on Google Cloud Big Data. Jurnal Teknik Dan Science, 4(3), 28–38.

DOI:
https://doi.org/10.56127/jts.v4i3.2358

Abstract: The development of the Adi Soemarmo Airport Train route is necessary to optimise its services by increasing the load factor. One of the efforts that can be made to enhance the load factor includes demand modelling. Big Data provided by Google Cloud Big Data is utilised for its capacity to provide fast and large-scale trip data. This approach supports demand modelling carried out across regencies and cities as study areas for route development. The data is modelled with a four-stage transportation model, adopting zones based on sub-districts within the regencies and cities in the study area. The results indicate the emergence of potential demand through changes in transit points to transfer points in zones along the Madiun, Klaten, Wonogiri, and Gundih. These zones that have potential demand are chosen as the guidelines for developing the Adi Soemarmo Airport Train route.

Keywords: Demand Modelling, Public Transportation, Google Cloud Big Data, Transport Engineering

INTRODUCTION

The Adi Soemarmo Airport Train is a rail-based public transportation service that currently connects Adi Soemarmo Airport and Surakarta City to Madiun. This service commenced operation on December 29, 2019, with the first route of Adi Soemarmo Airport and Klaten, and was transferred to Madiun on November 2, 2024. The initial route faced an inadequate performance, which was reflected by its load factor of 13%, as recorded by the Indonesian Directorate General of Railway, indicating that the passenger numbers were significantly below the train capacity provided, and the train operated in nearly empty conditions, which is considered to be wasting capacity [1]. Moreover, the vacant train becomes inefficient, as it potentially contributes to financial losses for the operator [2]. Accordingly, this situation necessitated research on route development, which encouraged the optimisation of Adi Soemarmo Airport Train services by increasing the load factor. Route development is focused on areas adjacent to the Adi Soemarmo Airport that offer the potential to accommodate train demand, including sub-districts in the Cities of Surakarta and Madiun, as well as the Regencies of Grobogan, Boyolali, Sragen, Karanganyar, Magetan, Wonogiri, Klaten, Ngawi, and Sukoharjo.

One effort to achieve an optimised load factor is to model the demand for a reviewed public transportation system [3]. People's mobility can be predicted through transportation demand modelling, which measures the level of public transportation utilisation using the load factor. Demand modelling requires these movement data, which can be obtained through conventional methods such as field surveys, including home interviews and roadside interviews. However, this method is certainly time-consuming and labor-intensive, as surveyors must make an effort to find respondents directly in the field [4]. On the other hand, the extensive scope of the region, which covers various regencies and cities, results in a huge amount of data, which also becomes another challenge [5]. In terms of public transportation planning, Big Data also offers the benefit of improving performance efficiency, which is enabled by the ability to understand customer needs [6]. Thus, Big Data, a more efficient source of various kinds of data, can be used as an alternative [7]. One of the Big Data providers is Google Cloud Big Data, which offers fast and large-scale data to support demand modelling. Therefore, demand modelling utilising Big Data based on Google Cloud is carried out to model the demand for the Adi Soemarmo Airport Train to expand its route.

RESEARCH METHOD

This study aims to forecast public transportation demand utilising big data from Google Cloud to map the further development of the Adi Soemarmo Airport Train route. Big data is an extensive and diverse aggregate of structured and unstructured data from various sources that continuously expands over time [8]. These data sets are particularly large and complex in terms of volume, velocity, and variety, making them beyond the capabilities of conventional data management systems [9]. In the transportation context, data can usually be obtained from mobile phones through telecommunications network operators or applications [10]. This data can be collected by selecting samples with detected movement activity, resulting in a dataset of various samples over a specific period [11]. In addition, data from Google Cloud uses Structured Query Language (SQL), which requires a coding process to convert it into the desired data [12]. This data enables the identification of users' behaviour through their movement patterns, allowing for the provision of transportation services that better suit their needs [7]. For the data requirements, this study is based on 181 sub-district-based zones across all regencies and cities, as portrayed in Figure 1.

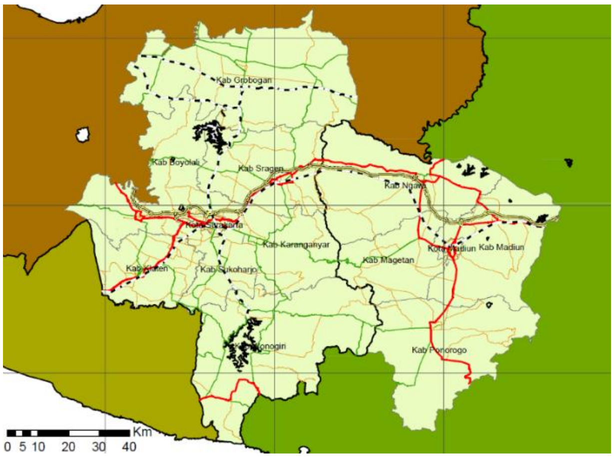


Figure 1. Map of the Study Area

Demand modelling in this study is trip-based, where it takes into account some attributes in accordance with the interaction between zones inside the study area, such as population and land use [13]. Therefore, this approach specifically utilises inter-zone movement characteristics data, including its quantity and travel time, obtained from Google

Cloud. From this data, mode choice can be modelled, alongside the corresponding origin-destination (OD) matrix, and demographic data is subsequently applied to generate the trip generation model. The modelling approach is the four-stage transportation model, where the sequence of stages can vary depending on the data and modelling objectives [14]. This study follows the sequence of trip generation, modal split, trip distribution, and trip assignment.

Trip Generation

This step estimates the number of movements leaving each zone based on modelling results, where the opposite direction is referred to as trip attraction.

Modal Split

This stage predicts the distribution of movement across available modes of transportation. Considering multimodal is necessary, as it can enhance the accuracy of demand prediction outcomes [15]. In this stage, a frequently used approach is the logit model, in which the probability of mode choice ($P_{(i)}$) is obtained using Equation 1, where $V_{(i)}$ represents the trip characteristic from the origin to the destination zone.

$$P_{(i)} = \frac{e^{V_{(i)}}}{\sum_j e^{V_{(j)}}} \qquad (1)$$

Trip Distribution

This stage involves allocating the number of trips between distinct zones, which is influenced by the resistance function ($f(C_{ij})$). The resistance function is the factor that can affect the occurrence of trips, such as travel time, distance between zones, and cost. Initially, a basic origin-destination (OD) matrix is compiled and iterated using the Gravity model. In this model, the trip frequency between two zones is directly proportional to the intensity of activity in the interacting zones and inversely proportional to the resistance factors between them [16]. This model is expressed in Equations 2 and 3, with the output representing the number of trips from origin zone i to destination zone d (T_{id}) and generally illustrated in a desire line map or a basic OD matrix, as demonstrated in Table 1.

$$T_{id} = k\frac{O_i\, D_d}{d_{id}^2} \qquad (2)$$

$$T_{id} \approx O_i\, D_d\, f(C_{id}) \qquad (3)$$

Note:
T_{id} = Number of trips from origin zone i to destination zone d
O_i, D_d = Number of generated trips from origin zone i; or attracted trips to destination zone d
d_{id} = Resistance between zone i and d (distance, travel time, or speed)
K = Constant
$f(C_{id})$ = Resistance function between zone i and d (distance, travel time, or speed)

Table 1. Basic Origin-Destination Matrix

Destination (d) / Origin (i)	Regency A			Regency B			O_i
	1	**2**	**3**	**4**	**5**	**6**	

Reg. B Reg. A	**1**	T_{11}	T_{12}	T_{13}	T_{14}	T_{15}	T_{16}	O_1
	2	T_{21}	T_{22}	T_{23}	T_{24}	T_{25}	T_{26}	O_2
	3	T_{31}	…	…	…	…	…	O_3
	4	T_{41}	…	…	…	…	…	O_4
	5	T_{51}	…	…	…	…	…	O_5
	6	T_{61}	T_{62}	T_{63}	T_{64}	T_{65}	T_{66}	O_6
	D_d	D_1	D_2	D_3	D_4	D_5	D_6	

Furthermore, the next stage involves modelling the potential for public transportation users based on the basic OD matrix, which, along with the proportion of public transportation mode choices, is iterated using the average method as defined in Equations 4 and 5, resulting in the public transportation OD matrix. This matrix subsequently becomes the OD matrix that is assigned to the public transportation network system during the trip assignment phase.

$$T_{id} = t_{id} \frac{E_i + E_d}{2} \qquad (4)$$

$$E_i = \frac{O_i}{o_i} \quad and \quad E_d = \frac{D_d}{d_d} \qquad (5)$$

Note:
T_{id} = Predicted future number of trips from origin zone i to destination zone d
t_{id} = Existing number of trips from origin zone i to destination zone d
E_i, E_d = Growth rate of zones i and d trip numbers
O_i, D_d = Predicted number of generated trips from origin zone i; or attracted trips to destination zone d
o_i, d_d = Existing number of generated trips from origin zone i; or attracted trips to destination zone d

Trip Assignment

This stage assigns the public transportation OD matrix to predetermined routes, resulting in an estimate of the utilisation volume of the transportation network, which includes road and rail networks.

This four-stage modelling is performed using the Emme 3.4 program. Furthermore, the result of the OD matrix assignment on the public transportation network system reflects the daily number of public transportation users. Public transportation routes across zones form a network that intersects at several transit points. At this point, passenger boarding and alighting activities take place, serving as both origin and destination points, as well as points of mode interchange, or transfer points. The transfer potential at each integrated transfer point signifies the potential of passengers using public transportation at a particular point [17].

RESULT AND DISCUSSION

Trip generation

Trip generation measures the potential individual movement to and from each zone, defined as the daily number of trips made, derived from the population of working-age residents from Google Cloud Big Data, as shown in Table 2 for the example in Boyolali and visualised in Figure 2 for the entire study area.

Table 2. Potential Trips Data Example of Boyolali Regency

Districts	Potential Trips (people/day)
Ampel	22438
Andong	33563
Banyudono	29198
Boyolali	40121
Cepogo	33046
Gladagsari	23449
Juwangi	19422
Karanggede	25229
Kemusu	18951
Klego	26275
Mojosongo	32646
Musuk	17621
Ngemplak	52940
Nogosari	39825
Sambi	26021
Sawit	17754
Selo	16529
Simo	27357
Tamansari	15908
Teras	28317
Wonosamodro	16833
Wonosegoro	21051

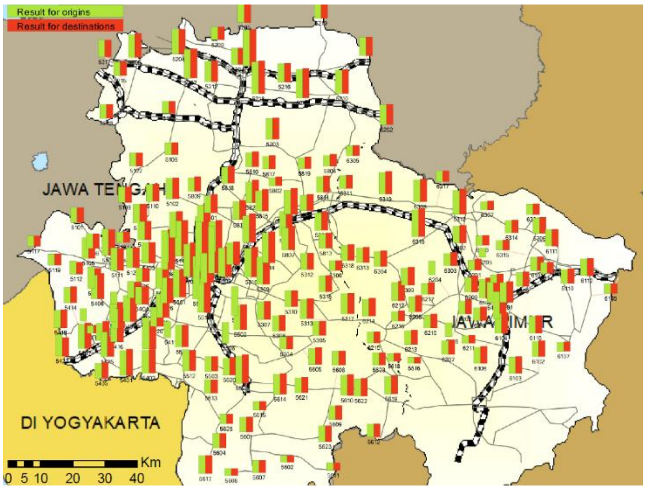


Figure 2. Illustration of Trip Generation and Attraction in the Study Area

Modal Split

This stage compares the probabilities between three modes, specifically passenger cars, motorcycles, and public transportation (PT), which are buses and trains in this case, across five routes originating from Surakarta, the city adjacent to Adi Soemarmo airport, specifically with the destinations to Madiun, Sragen, Wonogiri, Klaten, and Purwodadi, while featuring each characteristic to make a trip on these routes. Its characteristics obtained from Google Cloud Big Data are reviewed, including the route length from origin to destination, travel time, and speed, as detailed in Table 3. This information is possible to obtain due to their ability to access the appropriate source, from the government database, for instance, hence it creates a well-designed algorithm in their database, which is continuously calibrated and predicted [18]. As a result, identifying the characteristics is essential for determining the $V_{(i)}$ function to calculate the probability of mode choice using Equation 1 and travel time from Table 3 as the resistance function. The modelling outcomes are presented in Table 4 according to the characteristics of each origin, destination, and mode type.

Table 3. Three Modes Comparison of Origin-Destination Trip Characteristics

Origin	Destination	Distance (km)	Car		Motorcycle		Public Transportation	
			Travel Time (hours)	Speed (km/hour)	Travel Time (hours)	Speed (km/hour)	Travel Time (hours)	Speed (km/hour)
Surakarta	Madiun	113	1,68	67	2,60	43	1,53	74
Surakarta	Sragen	31,8	0,83	38	0,72	44	1,08	29
Surakarta	Wonogiri	36,8	1,10	33	0,95	39	1,77	21
Surakarta	Klaten	34,6	1,08	32	0,92	38	1,22	28
Surakarta	Purwodadi	65,5	1,83	36	1,53	43	2,25	29

Table 4. Three Modes Comparison of Modal Split Probability Results

Origin	Destination	P(car)	P(motorcycle)	P(PT)
Surakarta	Madiun	38%	20%	42%
Surakarta	Sragen	34%	37%	29%
Surakarta	Wonogiri	37%	41%	23%
Surakarta	Klaten	33%	37%	30%
Surakarta	Purwodadi	34%	42%	25%

Table 3 demonstrates that each route achieves distinct characteristics in terms of travel time and speed, regardless of distance, where the infrastructure quality is one of the significant factors that may influence these [19], hence affecting the probability results presented in Table 4. This table reveals that public transportation and motorcycles in five routes experienced fluctuations with each other, while car use remains relatively stable at approximately 35%. The Surakarta – Madiun route exhibits the highest probability of using public transportation (bus or train), while the potential for motorcycle usage is quite low in comparison to other routes. Travellers prefer public transportation (bus or train) over motorcycles on this route, at a ratio of 42:20, where its distance is the longest among the others. For shorter routes, the probability of using motorcycles is consistently the highest, while the probability of choosing public transportation is the lowest. One of the examples is the Surakarta – Wonogiri route, which spans 36,8 kilometres, experiences the lowest use of public transportation and the second highest of motorcycle use, with a ratio of 41:23 for motorcycle and public transportation.

Trip Distribution

Travel time (hours), distance (kilometres), and speed (kilometres per hour) are employed as factors influencing trip distribution. Inter-zone movement generation and attraction data, as well as trip resistance functions, acquired from Google Cloud Big Data, are applied with the Gravity model to obtain a basic origin-destination (OD) matrix. A basic OD matrix is generated for all zone pairs in the study area, resulting in a 181 x 181 matrix. Figure 3 presents an example of a Basic MAT measuring 22 x 22 exclusively in Boyolali Regency. Afterwards, this matrix is calculated within public transportation mode choice to obtain a public transportation OD matrix for trip assignment.

Regencies			Boyolali																					
	Disricts	Destinations	Ampel	Andong	Banyudono	Boyolali	Cepogo	Gladagsari	Juwangi	Karanggede	Kemusu	Klego	Mojosongo	Musuk	Ngemplak	Nogosari	Sambi	Sawit	Selo	Simo	Tamansari	Teras	Wonosamodro	Wonosegoro
	Origins	Zone Code	5101	5102	5103	5104	5105	5106	5107	5108	5109	5110	5111	5112	5113	5114	5115	5116	5117	5118	5119	5120	5121	5122
	Ampel	5101	0	166	191	501	651	1011	88	282	106	199	291	150	223	226	211	104	224	232	128	236	133	166
	Andong	5102	162	0	182	202	183	157	210	405	472	654	177	84	542	896	285	110	97	361	237	159	192	335
	Banyudono	5103	192	191	0	546	278	187	81	153	100	171	665	150	529	285	368	694	130	258	143	708	93	127
	Boyolali	5104	513	215	552	0	777	464	109	250	137	235	1353	428	479	298	310	264	278	351	195	1059	145	172
	Cepogo	5105	499	180	284	794	0	694	101	240	114	190	441	385	332	231	234	158	572	211	121	357	134	162
	Gladagsari	5106	774	163	194	474	704	0	82	212	95	164	286	178	233	217	191	106	250	208	117	233	112	138
	Juwangi	5107	86	211	78	104	102	83	0	158	223	164	70	45	176	178	92	48	52	113	70	57	135	142
	Karanggede	5108	274	402	146	237	253	234	157	0	230	794	133	93	282	315	206	88	115	303	197	106	386	569
	Kemusu	5109	104	476	97	111	117	98	223	233	0	358	96	53	245	293	128	59	59	173	110	93	153	193
	Klego	5110	195	659	166	217	198	176	164	805	358	0	182	86	326	429	260	101	97	434	294	159	241	619
Boyolali	Mojosongo	5111	311	169	624	1845	459	291	67	125	91	179	0	253	375	234	296	273	186	263	147	2144	85	93
	Musuk	5112	150	94	162	464	402	183	48	99	59	95	254	0	187	125	113	92	140	126	72	206	60	71
	Ngemplak	5113	225	540	488	441	312	225	174	286	238	324	406	166	0	1169	894	300	165	537	292	396	173	237
	Nogosari	5114	219	899	271	280	236	210	175	310	282	427	250	112	1183	0	536	165	124	628	381	231	169	269
	Sambi	5115	205	287	352	339	203	188	92	211	128	261	356	111	902	536	0	215	101	681	320	335	114	169
	Sawit	5116	106	117	700	269	155	104	49	93	60	104	301	86	328	176	220	0	75	156	87	296	57	77
	Selo	5117	230	104	134	285	583	260	54	121	62	101	186	137	175	133	114	77	0	116	66	153	69	84
	Simo	5118	228	367	251	318	225	208	113	309	174	435	269	113	545	626	685	152	109	0	1492	242	148	239
	Tamansari	5119	126	242	140	178	128	116	71	201	111	296	151	65	295	386	319	85	62	1497	0	135	93	154
	Teras	5120	225	178	762	799	327	216	81	111	101	174	1255	179	459	261	308	308	144	266	147	0	75	127
	Wonosamodro	5121	131	194	91	140	140	120	136	390	153	241	91	57	174	174	115	55	66	148	93	74	0	373
	Wonosegoro	5122	162	334	122	164	169	147	143	575	192	609	100	67	236	269	167	74	81	237	152	80	372	0

Figure 3. Partial Origin-Destination Matrix Example of Boyolali Regency

Trip Assignment

The trip assignment for the existing network, or before the development of the Adi Soemarmo Airport Train route, delineates the number of trips using each modelled route, consisting of the railway and road public transportation network in the study area. This is illustrated by Figure 4, which represents the number of trips as the thickness of the lines, meaning the thicker lines indicate a higher number of trips made in a route. This figure reveals that each route achieves various levels of public transportation demand, with the largest demand size observed on the Surakarta – Madiun route. This demand size signifies the urgent need for sufficient public transportation capacity, which will pose significant issues if inadequate, including passenger congestion and a high possibility of unserved [20]. Other routes with considerable traffic are the Surakarta - Klaten and Surakarta – Wonogiri routes. In other words, the potential demand for a route can be predicted with this approach, hence providing proper public transportation towards these directions.

Figure 4. Illustration of Existing Trip Assignment Result in the Study Area

Potential Demand in Transit Point

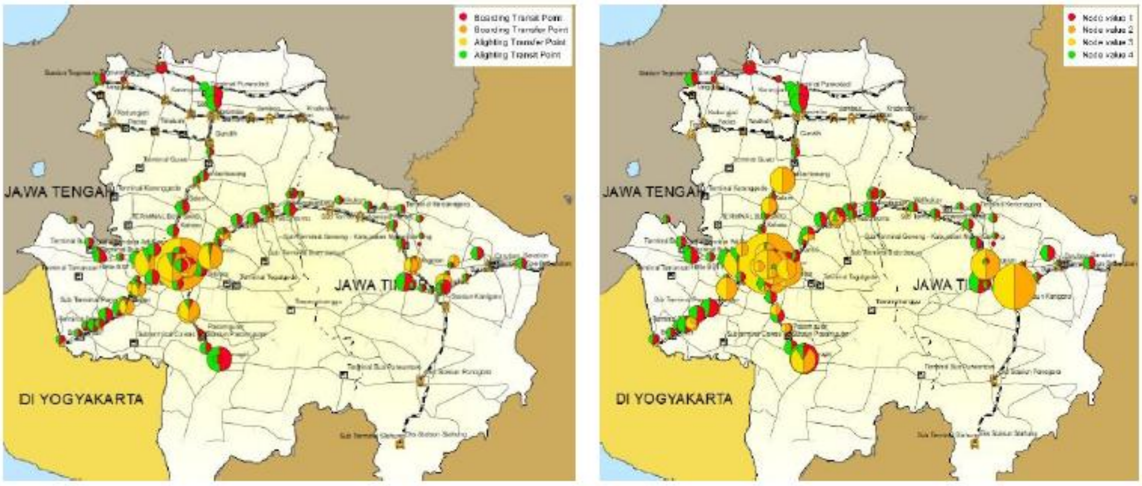
Improving the Adi Soemarmo Airport Train utilisation requires collaboration with other public transportation modes, aiming to increase transfer potential. Public transportation routes featuring many transfer points exhibit considerable synergy and connectivity with other public transportation, potentially increasing the number of users [21]. This can be possible as it offers alternatives to travel with multiple modes at once, where each modes have a different destination and its service range area, thus strengthening the accessibility of the area and the overall public transportation network [22]. Accordingly, transfer potential encourages understanding the synergy between current public transportation routes that intersect with the Adi Soemarmo Airport Train corridor. The existing public transportation routes in the study area connected with the planned development of the Adi Soemarmo Airport Train route include the existing route (Adi Soemarmo Airport – Klaten), Batara Kresna Train (Surakarta – Wonogiri), Solo – Klaten intercity bus, Surakarta – Madiun intercity-interprovince Bus, Surakarta – Purwodadi intercity bus, and Semarang - Surakarta intercity train.

Boarding and alighting activities at each point are determined through the performance of each intersecting existing public transportation route. This information will provide an overview of the potential passenger movements that may occur at each point, categorised into two types:

a. A transit point refers to a point or location, in this case a bus stop, station, or terminal, where passengers board or alight to begin or end their journey. For passengers boarding public transportation at this point, the journey they undertake is the first mile, beginning with the mode they use. Whereas for passengers disembarking at this point, the journey they undertake is the last mile, if they are using multiple modes.

b. A transfer point is designated as a point or location where passengers switch between different modes. At these points, passengers, who are changing modes, alight from the first mode and thereafter transfer to the following mode. This trip is neither the first nor the last mile of public transportation trips undertaken by the passenger.

The maps of potential passenger transfers at each transfer point in the study area, both before and after the development of the Adi Soemarmo Airport Railway route, are portrayed in Figure 5.



(Before) (After)

Figure 5. Comparison of Potential Passenger Transfers Before and After the Development of The Adi Soemarmo Airport Train Route

Figure 4 illustrates a circle representing the outcomes of passengers at each transfer point, which features red, orange, yellow, and green intersections. This symbology provides several important insights, including:

a. The red color (boarding transit point) reflects the number of passengers who begin their journey from a station.
b. The orange color (boarding transfer point) displays the number of passengers who board at a station after using another train service.
c. The yellow color (alighting transfer point) signifies the number of passengers who alight at a station to continue their journey on another train service.
d. The green color (allighting transit point) shows the number of passengers who end their journey at a station.

The size of the circle illustrates the intensity of the activity at that point, hence reflecting the proportion of the activity occurring.

Figure 5 also shows that several nodes previously serving as transit points have been converted into transfer points, seen in the color transition, from red-green to orange-yellow, signifying a shift from a transit point (the starting or ending point of a journey) to a transfer point (an interchange point). This shift also means an increase in the transfer process in a station, which is in line with the potential demand at these points and results in the emergence of new demand for the implementation of the Adi Soemarmo Airport Train development with new routes. The emergence routes, illustrated in Figure 5, are directed to Gundih and Wonogiri, which achieved a notable transformation from transit point to transfer point, establishing the new direction for the developments in response to increased demand at these stations. In addition, the route to Madiun deserves consideration, which experienced a significant improvement in transfer numbers, signifying the necessity of public transportation to this station, as the trip assignment stage also delivers similar results. Therefore, this condition is expected to increase along with the population and economic growth in the region that occurred during the operational period, as both growths are essential factors in contributing to the demand rise [23].

CONCLUSION

Results of demand modelling utilising Google Cloud Big Data reveal the potential demand through the conversion of transit points to transfer points. The prospective demand zones can be enhanced by extending the Adi Soemarmo Airport Train route to these areas. According to travel patterns and economic activity, four potential corridors for development are identified, namely from Adi Soemarmo Airport to Madiun, Klaten, Wonogiri, and Gundih. To optimise the potential demand rise, further development of areas serving as transfer points along the Adi Soemarmo Airport Train corridor is needed.

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