A Multidirectional Optimum Ecotope Base Algorithm Labour Central Java

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Abstract

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The workforce of Central Java Province in 2019 as many as 18.26 million has the potential to increase the economic growth of Central Java Province by increasing Labour productivity. Labour productivity will increase through the role of education and health. Education and health of workers, which are components of human capital, which in fact are inherent in the workforce. Problems will arise when the workforce experiences health problems. The purpose of this study was to analyze the spatial interaction patterns of Labour in Central Java Province. This research method uses the Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) approach to analyze the spatial interaction patterns of the workforce of Central Java Province by using a spatial weight matrix of euclidean distances. This study uses spatial panel data from 29 districts and 6 cities in Central Java Province from 2014 to April 2020. The results of this study indicate the variables that affect the economic growth of Central Java Province are spatial lag (ρ), capital, average length of schooling (RLS), spatial weight matrix with Euclidean Distance Labour with ρ value less than 5%. The results of this study showed that there was a strong change in the spatial interaction pattern of the workforce between 2014 and April 2020. Initially in 2014 there were 11 districts / cities with strong spatial interaction patterns of Labour, then in April 2020 there were only 5 districts city. The strong spatial interaction pattern of Central Java's workforce has decreased in April 2020, presumably due to government policies regarding activity restrictions in the form of social distancing and physical distancing policies

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INTRODUCTION

The Labour problem in Central Java Province is the mobility of Labour concentrated in certain regions. Labour mobility is influenced by the closest distance from the home location to the workforce's workplace. This research adopts the Solow (1956) economic growth model which, emphasising the importance of capital and Labour in economic growth. Then this study also considers the educational role of Mankiw et al's economic growth model. (1992) and the health role of Knowles and Owen's (1995) economic growth model. Mankiw et al's economic growth model. (1992) and the growth model Knowles and Owen (1995) develop the Solow (1956) economic growth model. Education and health are inherent in the workforce. Furthermore, with the abundance of human capital, the workforce crew force will migrate.

The novelty in this study uses A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) approach from Aldstadt and Getis (2006) using the spatial weight matrix of Euclidean Distance. Euclidean distance is used to solve existing problems related to geographical distance, Labour mobility, information mobility, and transportation mobility. Euclidean distance uses the X coordinate point and the Y coordinate point of a district and city in Central Java Province.

The problem of this research is whether there is a pattern of spatial interaction of workers from 29 districts and six cities in Central Java Province. The problem in this study was solved by calculating Global Moran's I using the spatial weight matrix of Euclidean Distance with the A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) analysis approach. This study adopts the spatial weight matrix of Euclidean Distance from Dattorro (2010), and adopts A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) approach from Aldstadt and Getis (2006). A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) is a procedure designed for clustering (grouping) spatial entities using ecotope empirical data. An ecotope is a collection of spatial entities having

the same characteristics based on local spatial autocorrelation statistics. A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) identifies spatial clusters using a spatial weight matrix using empirical data. This study uses a spatial weight matrix of Euclidean distance from Dattorro (2010) to calculate global Moran's I and Local Moran's I.

This study focuses on the workforce of Central Java Province in the form of spatial interaction patterns of Central Java Province workers from 2014 to April 2020. This study aimed to analyze the spatial interaction patterns of Labour between 29 districts and six cities in Central Java Province. This study analyzes the pattern of spatial interactions from the beginning of the observation year, 2014, and the end of the year 2020. The spatial interaction pattern is calculated using the Global Moran Index and the Local Moran Index. The Global Moran Index is used to determine global spatial interaction patterns in Central Java Province. The Moran Local Index is used to determine the local spatial interaction pattern between districts or cities in Central Java Province.

The workforce of Central Java Province in 2019 was 17.44 million of the total population of Central Java in 2019 of 26.21 million. There is 819,265 open unemployment in Central Java Province, meaning that 819 thousand people are still looking for work. The mobility of workers in Central Java Province in 29 districts and six cities in Central Java Province is high. The horizontal Labour mobility evidences this in the form of Labour migration from one districs or city to another. Labour migration in Central Java Province is suspected to be due to open unemployment due to the absence of job vacancies according to the required criteria.

Table 1 shows the number of workers in Central Java Province by education level. Based on the level of education completed in 2019, the workforce of Central Java Province mostly graduated from elementary school, 28%, and workers graduated from junior high school 20%. The workforce with a university education level is only 9%. This means that workers with low levels of education are considered to work in the non-

formal sector that does not require a lot of expertise. The problem in this study is that the workforce of Central Java Province is mostly workers with low education and specific skills. Workers with low education will look for job offers according to their educational needs and specific abilities to migrant workers to other areas searching for work. This labour migration forms a pattern of labor spatial interaction.

Central Java Province workers who migrate to other areas are suspected to be workers with low education who have specific skills. Workers with intense education will look for job vacancies according to the abilities and education of the workforce. Workers with low education in Central Java province mostly work as labourers with a high school education level in 2019. There are 3,643,535 workers. The general criteria for working in a factory require workers with high school education. Workers with low education and specific skills will create a pattern of labour spatial interaction in labour migration from one region to another. This study formulates how the pattern of spatial interaction of workers in Central Java Province.

Table 1. Central Java Province Workforce Based on Education Level in 2019

| Level Education	Total	Percentage
Never went to school	571.071	3%
Not completed in primary school	2.386.421	13%
Primary school	5.242.628	28%
Junior high school	3.643.535	20%
High school	2.382.579	13%
Vocational high School	2.395.187	13%
Diploma I/ Diploma II/ Diploma III	400.023	2%
University	1.595.075	9%
	18.616.519	**100%**

Source: BPS, 2020

Workers who migrate to other areas will form a pattern of labor spatial interaction. It is suspected that workers who carry out spatial interaction patterns are workers who have education in accordance with the criteria and skills needed, namely workers with an education level of elementary school graduates, 28% of the total number of workers in Central Java, and workers with a secondary school education level. First, there are 20% of the total workforce of Central Java Province. It is suspected that workers with an elementary school education level and workers with a junior secondary education level migrate to other areas because they work in the private sector and the trade sector. Workers with a high school education level make up 13% of the total workforce in Central Java. The pattern of spatial interaction between regencies/cities within the Central Java Province is thought to occur because the workforce works as laborers or factory employees. They work outside the area to earn additional income.

Figure 1 shows the labour migration of Central Java Province. Labour migration in Central Java province is thought to be due to the mobility of workers. Labour migration is indicated by the number of workers in Central Java Province in 2019, especially those who work as labourers and employees, namely 6.6 million workers. Workers with the status of workers and employees will work in regencies and cities with higher income levels than those in the area of origin. Central Java Province workers will then be self-employed workers as many as 3.3 million workers. The mobility of workers in Central Java Province is thought to be because there are 6.6 million workers because they want to earn a higher income than their area of origin.

Labour migration is suspected to be due to the mobility of workers. Labour migration is indicated by the number of workers in Central Java Province in 2019, primarily working as Labourers and employees, there are 6.6 million people. Workers with status as labourers and employees will work in districts and cities with an income level higher than their income in the area of origin.

Figure 1. Labor by employment status
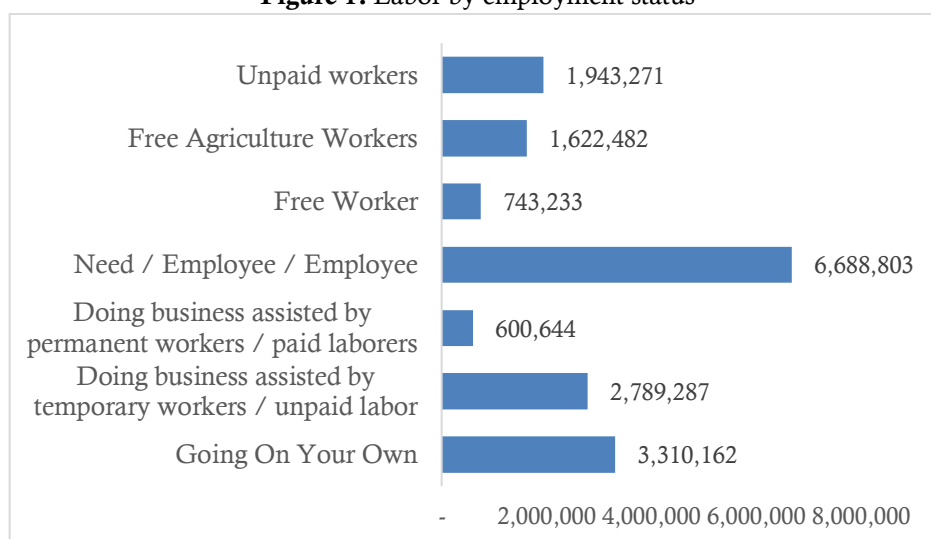
Source: BPS Data, 2020

Figure 1 shows the number of workers based on employment status whether the work is self-employed, workers work for other people. Workers who work with their own business do not get wages. Workers who work for others will get paid.

RESEARCH METHODS

This study uses Explanatory Spatial Data Analysis (ESDA) with the weight matrix approach of Euclidean Distance to calculate Spatial Autocorrelation (Global Moran's I and Local Moran's I). Spatial autocorrelation uses to answer how to analyze the spatial interaction patterns of Labour between districts and cities in Central Java Province. The use of the spatial weight matrix Euclidean Distance used in this study is to correct the weaknesses of using the weight matrix calculated based on distance and time. The use of transportation modes, the speed of information mobility, the rate of transportation mobility can be solved using the Euclidean Distance weight matrix. The Euclidean Distance weight matrix uses the X coordinate points and Y coordinate points of an entity.

The problem of this research is whether there is a pattern of spatial interaction of workers from 29 districts and six cities in Central Java Province. The problem in this study was solved by calculating Global Moran's I using the spatial weight matrix of Euclidean Distance with the A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) analysis approach. This study adopts the spatial weight matrix of Euclidean Distance from Dattorro (2010), and adopts A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) approach from Aldstadt and Getis (2006). A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) is a procedure designed for clustering (grouping) spatial entities using ecotope empirical data. An ecotope is a collection of spatial entities having the same characteristics based on local spatial autocorrelation statistics. A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) identifies spatial clusters using a spatial weight matrix using empirical data. This study uses a spatial weight matrix of Euclidean distance from Dattorro (2010) to calculate global Moran's I and Local Moran's I. This study focuses on the workforce of Central Java Province in the form of spatial interaction patterns of Central Java Province workers from 2014 to April 2020.

Table 2. Variable Description

No.	Variable	Indicator	Unit	Sources
1.	District / City Economic Growth	Regency / City GRDP	Rp	BPS Central Java
2.	Capital stock	Domestic Fixed Capital Formation (PMTB)	Rp	BPS Central Java
3.	*Human capital spillover* a. Average length of school (RLS)	Average length of school	years	BPS Central Java
	b. Labour	Residents aged 15 years and over who worked during the past week according to the highest education completed (not / not yet attending university) in the country	Person	BPS Central Java

Source: BPS Data, 2020

This study uses local spatial statistics, often referred to as Local Indicators of Spatial Association (LISA). Anselin (1995) defines statistical LISA must meet the requirements that the LISA for each observation provides an indication of the spatial grouping of similar values around the observations and the sum of all LISAs for all observations is proportional to global indicators. Local spatial autocorrelation indicates individual contribution to global spatial autocorrelation.

Local spatial autocorrelation is the value observed that i is positive (has similarity) or negative (different) with neighboring observations, j. Moran index value is between $-1 \leq |I| \leq 1$. This study adopted the Local Moran I statistic from Anselin (1995). Moran's-I-statistical model of local spatial autocorrelation was written,

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{ij}(x_j - \bar{X}) \quad \text{...............} \quad (1)$$

Where:

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} w_{ij}(x_j - \bar{x})^2}{n-1} \quad \text{...............} \quad (2)$$

$$Z_{I_i} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \quad \text{...............} \quad (3)$$

$$E_{I_i} = -\frac{\sum_{j=1, j \neq i}^{n} w_{ij}}{n-1} \quad \text{...............} \quad (4)$$

$$E[I^2] = A - B \quad \text{...............} \quad (5)$$

$$A = \frac{n - b_{2_i} \sum_{j=1, j \neq i}^{n} w_{i,j}^2}{n-1} b_{2_i} \quad \text{...............} \quad (6)$$

$$B = \frac{(b_{2_i} - n) \sum_{k=1, k \neq i}^{n} \sum_{h=1, h \neq i}^{n} w_{i,k} w_{i,h}}{(n-1)(n-1)} \quad \text{...............} \quad (7)$$

$$b_{2_i} = \frac{\sum_{i=1, i \neq j}^{n} (x_i - \bar{X})^4}{\left(\sum_{i=1, i \neq j}^{n} (x_i - \bar{X})^2\right)^2} \quad \text{...............} \quad (8)$$

$$V_{I_i} = E[I_i^2 - E[I_i]^2] \quad \text{...............} \quad (9)$$

Where, I_i is Local Moran's-I-statistic; N is 29 regencies; $\bar{x}$ is average value of x; x is Observation Variables; w_{ij} is elements of the spatial weight matrix (the spatial weight matrix) that connects the observations of district/city i (observed districts/cities) with neighboring districts/cities, j using an inclusive distance approach based on the x-coordinate point and the y-coordinate point of a district/city.

This study uses a spatial weight matrix with Euclidean Distance to calculate Global Moran I. Global Moran I is used to analyze overall or global spatial autocorrelation (Cliff and Ord, 1981). Positive spatial autocorrelation occurs when geographically tends to be surrounded by neighbors with the same value of the variables studied. Negative spatial autocorrelation occurs when geographically tends to be surrounded by neighbors with different values of the variable under study. This study adopted the Global Moran I statistics from Anselin (1995).

The Global Moran's Index equation is written:

$$I = \frac{N}{S_0} \frac{w(i,j)(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \quad \text{...............} \quad (10)$$

Where, N is the number of times observed (8 years), S_0 is standardization of data, x is observed variable, i is 29 districs and 6 cities in Central Java, j is neighboring region, $\bar{x}$ is average from x_i,

$$\bar{x} = \sum_{i=1}^{N} \frac{x_i}{N} \quad ....(11)$$

$$S_0 = \sum_{i=1}^{N} \sum_{j=1}^{N} w(i,j) \quad ....(12)$$

Where, is spatial weight connectivity *i* and *j*; $w(i,j)$ is matrix value N x N, $w(i,j)$ *is* $A/d(i,j)^m$ where d (i, j) is the distance from point i to point j, m is 2 (the x coordinate point and the y coordinate), $A = 1$, *Expected Value* (I) = $-1/(N-1)$

A positive Global Moran's Index value shows that the observed region has similarities with its neighbouring areas. On the other hand, a negative Global Moran's Index value indicates that the observed area has no similarities with its adjacent regions. Moran's index values between $-1 \leq |I| \leq 1$. Decision making is significant if H_ (0) is rejected. It means that there is autocorrelation between 29 districts and six cities in Central Java Province.

RESULTS AND DISCUSSION

Several researchers on the spatial pattern of human activity have been carried out, including Ma et al., 2013; Hasan and Ukkusuri, 2014; Liu et al., 2015. Ma, Wu et.al, (2013) used the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to identify public transport travel patterns from historical smart card records. The results of research by Ma, Wu et.al, (2013) revealed that there is a spatial pattern of individual daily trips through the dataset of public transport passengers. Hasan and Ukkusuri's (2014) research uses a data set of Twitter check-in locations to identify patterns of urban spatial activity. Liu, Gong et.al., (2015) explore the structural pattern of the Shanghai city using massive taxi travel data through exploring the impact of different land use characteristics on travel patterns.

Research on labor migration has been carried out by Ge, Long et.al., (2020); Critelli, Lewis et. al., (2021); Deng, Zhang et.al., (2020); Howard (2020), and Mueller, Sheriff et.al., (2020), dan Chen, Gong et.al., (2020). Ge, Long et.al., (2020) research was conducted in Yucheng City, China. The results of Ge, Long et.al., (2020) research note that at first labor migration in Yucheng City, China, occurred in young people who urbanized from villages to cities. However, after technological advances in the agricultural sector, the number of workers working in cities decreased. The city of Yucheng has transformed from traditional agriculture to agriculture that uses modern technology so that the number of workers working in the city is reduced. The city of Yucheng is transforming to create job opportunities for local residents so that migrant workers who come to the city can return to work in the village by starting a business in the village.

The results of research from Critelli, Lewis (2021) show that labor migration in Kyrgyzstan as a former colony of the Soviet Union changes the way the Kyrgyz population thinks to make decisions about migrating workers to other countries. Kyrgyzstan's population migration occurred because of the poverty that hit the country of Kyrgyzstan. Individual families in the country of Kyrgyzstan compromise to decide which family members migrate to the country, and which family members remain at home.

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Deng, Zhang et.al., (2020) conducted a survey of labor migration throughout East China, South China, and West China using geodetectors to determine the stability index of labor migration between cities, and migration between industries between cities. The results of Deng, Zhang et.al., (2020) research show that all cities in eastern China have a high migration stability index with the driving force of the surrounding villages. All cities in eastern China have an appeal in the industrial sector. Personal relations between workers increase the stability of labor migration.

The results of Howard's research (2020) are known that high labor mobility will cause disparities between regions. Labor migration will reduce the unemployment rate of labor-receiving cities through increased demand for housing by migrant workers. Labor migration shows changes in labor mobility patterns that vary.

Research by Mueller et.al.,(2020) in African countries shows that labor migration out of East African countries caused by climate change that occurs in African countries forms the pattern of labor migration in East Africa. East Africa's 10 percent decrease in rainfall led to a 12 percent decrease in labor migration out of East Africa.

Chen, Gong et.al., (2020) research on the impact of weather disturbances on labor mobility in urban areas using location-based service data from Baidu maps. The results of the research by Chen, Gong et.al., (2020) show that variations in labor spatial mobility occur because the functions of urban areas are different from one another. The functions of the city differ from one another in the use of transportation, recreational facilities, institutions, commercial facilities, and residential facilities.

Silero research (2021) to identify separately from the nearest neighbor index clustering (NNIC). Grouping of local points by using neighboring relationships. Sillero (2021) uses Delaunay triangulation among all points to calculate the length of all lines, and chooses the shortest line from the expected nearest neighbor distance. The points that intersect the selected Delaunay line are considered to belong to an independent cluster.

A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) was first developed by Getis and Aldstadt (2004). A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) is a good tool for recognizing spatial associations among nearby units. Base A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) was used to test the presence of spatial associations between nearby spatial units. Model A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) uses a spatial weight matrix to represent the spatial association of observed data. A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) uses a weight matrix with a contiguous type that considers the spatial associations in each region. The weight matrix in the spatial model is represented as a function of decreasing distance, adjacent spatial units, spatial associations in a data set A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) using a vector that distinguishes nonspatial units from spatially related units.

Research on AMOEBA (Algorithm Based Optimum Multidirectional Ecotope) has been carried out by Duque, Aldstadt et al., (2010); and Estivill and Lee (2020). The research of Duque, Aldstadt et.al., (2010) adopted an algorithm called AMOEBA (Algorithm Based Optimum Multidirectional Ecotope) from Aldstadt and Getis (2006) on an empirical study of georeferenced socio-demographic data in Accra, Ghana using rook contiguity in the Python application program. The results of research from Duque, Aldstadt et.al., (2010) note that the spatial distribution of the data affects the running time, the larger the ecotopes, the greater the running time, and the greater the variance. The ability of AMOEBA can be used to identify irregular ecotopes.

A similar study was conducted by Estivill and Lee (2020) who used AMOEBA (Algorithm Based on Optimum Multidirectional Ecotope) from Aldstadt and Getis (2006) to explore the spatial data of electromagnetic media using Delaunay diagrams. Research results from Estivill and Lee (2020) show that clustering methods that represent proximity such as rasters or vectors are not suitable for spatial clusters.

Research on spatial autocorrelation has been investigated by Hu, Chun et.al., (2020); Gu, Jie et.al., (2020); Gu, Meng et.al., (2020);Hu, Chun et.al., (2020) conducted a study of mixed patterns of spatial autocorrelation of breast cancer incidence in Broward State of Florida from 2000 to 2020 using different model specifications. Research results Hu et. al., (2020) it is known that the spatial filtering of eigenvectors from the Moran index gives the flexibility of the method. The research of Gu, Jie et.al., (2020) uses spatial panel data from dynamic survey data of Chinese migrants from 2014 to 2017 to examine the spatial distribution pattern of migrant workers towards floating city settlements.

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The research of Gu, Meng et.al., (2020) uses a 2015 national survey from 31 provinces in China to determine the distribution pattern of the educated workforce using a spatial autocorrelation model. The research results of Gu et. al., (2020) it is known that the impact of human capital spillover comes from special policies from each province related to the existence of social network relationships.

In contrast to research from Hu et.al., (2020); Gu, Jie et al. (2020), and Gu, Meng et.al.,

(2020), research from Gu, Yu et.al., (2020) used the Multiscale Geographically Weighted Regression (MGWR) model to conduct research in 2015. The results of Gu's research, Yu et.al., (2020) note that the MGWR calculations identify significant spatial non-stationary results in determining the distribution measurement in the Chinese city. This is influenced by the number of GDP per capita, beds per 10,000 inhabitants, and public financial expenditures. A similar study was conducted by Bao, Yang et.al., (2021) who used the Geographically Weighted Poisson Regression (GWPR) method to identify the relationship between various factors that influence accidents, and regional accident frequency in New York City. How is the spatial impact of human activities on traffic accidents The results of his research note that human activities in New York City significantly affect the spatial pattern of urban traffic accidents.

The novelty of this research is to correct the use of a spatial weight matrix that uses mileage. This study uses the Euclidean Distance spatial weight matrix. Advances in technology, advances in transportation modes can overcome the problem of travel time. For example, the distance from Semarang to Jakarta is 442.1 km. The distance from Semarang to Jakarta can be reached by land transportation and air transportation. The use of air transportation of aeroplanes takes more time than using the train land transportation mode. The distance from Semarang to Jakarta using air transportation mode only takes 45 minutes, while the travel time from Semarang to Jakarta using rail transportation mode takes 6 hours. The distance from Semarang to Jakarta by bus takes 10 hours. The Euclidean Distance spatial weight matrix solves problems related to the issues with modes of transportation, distance, travel time. The Euclidean Distance spatial weight matrix uses X coordinates and Y coordinates to determine an entity. A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) uses the Euclidean Distance spatial weight matrix to calculate the Global Moran's Index.

The spatial weight matrix uses to determine the proximity of regions to one another because the closer areas will have a more significant effect than the more distance areas

(Anselin, 1988). The way to obtain a spatial weighting matrix or spatial weighting (W) is to use The information on the distance of the X coordinate point and the Y coordinate point from the neighbourhood, or the proximity between one region to another based on the Euclidean Distance approach (Dattorro, 2010).

The use of Euclidean Distance to make calculations easier. The value of Euclidean Distance obtain from the Central Java.shp map processed through GeoDa, then from the Central Java shp map the x coordinate point and the y coordinate point will be obtained. Euclidean Distance is in mills. One Euclidean Distance = 15.91 km. Calculation of the spatial weight matrix with the Euclidean Distance approach using GeoDa version 1.18. which launching October 2020. Table 3. identifies the x coordinate points and y coordinate points of 29 districts and 6 cities in Central Java Province. Table 3 shows the existence of the euclidean distance weight matrix using the x coordinate point and the y coordinate point from 29 districts and six cities in Central Java Province. The use of the euclidean distance spatial weight matrix to solve proximity, time, Labour mobility, and information mobility. Semarang City with coordinate point x 110.4 and coordinate point y -7.2.

Table 3. Spatial Weight Matrix with Euclidean Distance

No	Regency and City	The X Coodinate Point	The Y Coordinate Point
1	Cilacap	108.8	-7.4
2	Banyumas	110.6	-6.9
3	Purbalingga	110.9	-7.1
4	Banjarnegara	109.6	-7.3
5	Kebumen	109.1	-7.4
6	Purworejo	109.8	-7.0
7	Wonosobo	111.3	-70
8	Magelang	110.6	-7.4
9	Boyolali	108.9	-7.0
10	Klaten	110.2	-7.4
11	Sukoharjo	110.7	-6.5
12	Wonogiri	111.0	-7.6
13	Karanganyar	109.6	-7.6
14	Sragen	110.1	-7,04

No	Regency and City	The X Coordinate Point	The Y Coordinate Point
15	Grobogan	110.6	-7.6
16	Blora	110.2	-7.5
17	Rembang	111.0	-6.7
18	Pati	110.5	-7.7
19	Kudus	109.6	-6.8
20	Jepara	110.3	-7.0
21	Demak	110.8	-7.5
22	Semarang	109.1	-6.8
23	Temanggung	109.6	-7.0
24	Kendal	109.4	-7.0
25	Batang	109.4	-7.0
26	Pekalongan	109.1	-7.0
27	Pemalang	110.1	-7.0
28	Tegal	110.9	-7.2
29	Brebes	109.91	-7.4
	Cities		
30	Magelang	109.4	-7.3
31	Surakarta	109.9	-7.7
32	Salatiga	111.4	-6.7
33	Semarang	110.4	-7.2
34	Pekalongan	110.9	-7.3
35	Tegal	110.8	-7.6

Source: Data processed with Geode Version 1.18.

Table 4 shows the spatial weight matrix of labor using Euclidean Distance in 2014, and in 2020. It appears that Banjarnegara Regency, Batang Regency, Blora Regency Pekalongan City, Pekalongan Regency, Temanggung Regency, Wonosobo Regency, Purworejo Regency, Rembang Regency, Sragen Regency and Sukoharjo Regency have a negative z coefficient value and the Euclidean Distance spatial weight matrix of the workforce (Wz) negative in 2014, and 2020. This indicates that Labor Banjarnegara Regency, Labor Batang Regency, Labor Blora Regency, Labor Pekalongan City, Labor Pekalongan Regency, Labor Temanggung Regency, Labor Wonosobo Regency, Labor Purworejo Regency, Labor Rembang Regency, Labor Sragen Regency, and Labor Sukoharjo Regency spread or diverge. The workforce of Banjarnegara Regency, Labor Batang Regency, Labor Blora Regency, Labor Pekalongan City,

Labor Pekalongan Regency, Labor Temanggung Regency, Labor Wonosobo Regency, Labor Purworejo Regency, Labor Rembang Regency, Labor Sragen Regency, and Labor Sukoharjo Regency spreads or diverges.

Table 4 shows the spatial weight matrix of labor using Euclidean Distance. It appears that Labor Cilacap Regency, Labor Demak Regency, Labor Banyumas Regency, Labor Semarang City, Labor Semarang Regency have a positive z coefficient value and a positive Euclidean Distance weight matrix of labor (Wz) in 2014, and 2020. This identifies that Labor Cilacap Regency, Labor Demak Regency, Labor Banyumas Regency, Labor Semarang City, Labor Semarang Regency cluster or converge.

Table 4. Labour Spatial Weight Matrix with Euclidean Distance.

No	Regency / City	L2014		L2020	
		z	Wz	z	Wz
1	Cilacap Regency	1,272	1,181	1,484	1,581
2	Demak Regency	0,147	0,676	0,377	0,997
3	Grobogan Regency	1,184	-0,237	1,194	-0,321
4	Banjarnegara Regency	-0,081	-0,144	-0,138	-0,075
5	Banyumas Regency	1,281	0,489	1,568	0,681
6	Batang Regency	-0,683	-0,814	-0,511	-0,633
7	Blora Regency	-0,362	-0,005	-0,858	-0,858
8	Boyolali Regency	0,111	0,398	0,258	-0,513
9	Brebes Regency	1,415	-0,754	1,549	-0,551
10	Magelang City	-2,304	0,116	-2,067	0,334
11	Jepara Regency	-0,343	-0,363	0,661	-0,053
12	Karanganyar Regency	-0,326	-0,422	-0,172	-0,289
13	Kebumen Regency	-0,686	-0,815	0,475	-0,138
14	Kendal Regency	-0,133	0,296	-0,011	0,271
15	Klaten Regency	0,551	-0,484	0,528	-0,341
16	Magelang Regency	-0,649	-0,236	1,171	-1,553
17	Pati Regency	0,594	-0,363	0,535	-0,053
18	Salatiga City	2,041	0,338	-1,871	-0,601
19	Pekalongan City	-1,861	-0,566	-1,666	-0,371
20	Semarang City	1,716	0,899	2,048	0,248
21	Surakarta City	-1,254	-0,041	-1,098	0,049
22	Tegal City	-0,622	1,421	-1,813	1,311
23	Kudus Regency	-0,363	0,361	-0,534	0,524
24	Pekalongan Regency	-0,448	-0,526	-0,292	-0,464
25	Pemalang Regency	0,519	-0,068	0,449	0,121
26	Tegal Regency	0,536	-0,036	0,712	0,062
27	Temanggung Regency	-0,415	-0,537	-0,438	-0,512
28	Wonogiri Regency	-0,109	-0,318	0,298	-0,183
29	Wonosobo Regency	-0,521	-0,422	-0,428	-0,471
30	Purbalingga Regency	-0,293	0,573	-0,121	0,626
31	Purworejo Regency	-0,771	-0,552	-0,553	-0,428
32	Rembang Regency	-1,005	-0,361	-0,858	-0,852
33	Semarang Regency	0,256	1,289	0,377	0,145
34	Sragen Regency	-0,237	-0,132	-0,172	-0,071
35	Sukoharjo Regency	-0,309	-0,229	-0,194	-0,109

Source: Processed Data, 2020

Figure 2. Map of LISA Clusters for Workers in Central Java Province in 2014.

Source: Processed Data, 2020

Figure 2 shows a map of the 2014 labor force Lisa Cluster Labor Batang Regency, Labor Blora Regency, Labor Magelang City, Labor Karanganyar Regency, Labor Pekalongan City, Labor Pekalongan Regency, Labor Wonosobo Regency, Labor Purworejo Regency, Labor Rembang Regency are included in the Cold Spot. The districts and cities included in the LISA Cluster Labor Hot Spot map are Cilacap Regency, Demak Regency, Banjarnegara Regency, Banyumas Regency, Jepara Regency, Kebumen Regency, Pati Regency, Semarang

City, Pemalang Regency, Tegal Regency, Temanggung Regency, and Semarang Regency.

Figure 3. Map of LISA Clusters for Workers in Central Java Province in 2020

Source: Processed Data, 2021

Figure 3 shows a map of the Lisa Cluster workforce in 2020 Labor Demak Regency, Labor Blora Brebes Regency, Labor Magelang City, Labor Kudus Regency, Labor Pemalang Regency, Labor Temanggung Regency, Labor Wonosobo Regency, Labor Purworejo Regency are included in the Cold Spot. The districts and cities included in the LISA Cluster Labor Hot Spot map are Cilacap Regency, Banyumas Regency, Batang Regency, Blora Regency, Rembang Regency and Semarang City.

Table 5. Pattern of Strong Spatial Interaction (LISA) of Workers in Central Java in 2014.

2014			
HH	**LH**	**LL**	**HL**
Cilacap Regency	Kendal Regency	Batang Regency	Grobogan Regency
Demak Regency Banjarnegara Regency	Salatiga City	Blora Regency	Boyolali Regency
	Surakarta City	Magelang City	Brebes Regency
Banyumas Regency	Tegal City	Karanganyar Regency	Klaten Regency
Jepara Regency	Kudus Regency	Pekalongan City	Magelang Regency
Kebumen Regency	Purbalingga Regency	Pekalongan Regency	Wonogiri Regency
Pati Regency	Sragen Regency	Wonosobo Regency	
Semarang City	Sukoharjo Regency	Purworejo Regency	
Pemalang Regency		Rembang Regency	
Tegal Regency			
Temanggung Regency			
Semarang Regency			

Source: Processed Data, 2021

Table 5 and Table 6 identify a change in the pattern of spatial interaction of workers in 2014, and 2020. Initially in 2014 Demak Regency, Temanggung Regency, Pemalang Regency with high labor characteristics interacted spatially with regencies/cities with high workforce characteristics. but in 2020 it appears that Demak Regency, Temanggung Regency, Pemalang Regency with low labor characteristics interact spatially with regencies/cities with low labor characteristics. Changes in the spatial interaction pattern of Banjarnegara Regency, Pati Regency and Semarang Regency workers occurred in 2014,

and 2020. Initially in 2014 Banjarnegara Regency, Pati Regency and Semarang Regency with high workforce characteristics interacted spatially with districts/cities with high labor characteristics the workload is high but in 2020 it appears that Banjarnegara Regency, Pati Regency and Semarang Regency with low labor characteristics interact spatially with regencies/cities with high labor characteristics. Changes in the pattern of spatial interaction of the workforce in Jepara Regency, Kebumen Regency and Tegal Regency occurred in 2014, and 2020. Initially, in 2014 Jepara Regency, Kebumen Regency and Tegal Regency with high

labor characteristics interacted spatially with the regency/city with high labor characteristics. The workload is high but in 2020 it appears that Jepara Regency, Kebumen Regency and Tegal

Regency with high workforce characteristics interact spatially with regencies/cities with low labor characteristics.

Table 6. Pattern of Strong Spatial Interaction (LISA) of Workers in Central Java in 2020

2020			
HH	**LH**	**LL**	**HL**
Cilacap Regency	Banjarnegara Regency	Demak Regency	Grobogan Regency
Banyumas Regency	Kendal Regency	Brebes Regency	Boyolali Regency
Batang Regency	Klaten Regency	Magelang City	Jepara Regency
Blora Regency	Pati Regency	Kudus Regency	Karanganyar Regency
Rembang Regency	Salatiga City	Pemalang Regency	Kebumen Regency
	Pekalongan City	Temanggung Regency	Tegal Regency
	Pekalongan Regency	Wonosobo Regency	Purbalingga Regency
	Wonogiri Regency	Purworejo Regency	Sukoharjo Regency
	Semarang City		Magelang Regency
	Sragen Regency		
	Semarang Regency		
	Surakarta City		
	Tegal City		

Source: Processed Data, 2020

A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) is calculated using the Global Moran's Index. The Global Moran's Index represents the spatial interaction pattern of the Central Java Province workforce. Structure of spatial interaction patterns in the form of labour migration between 2014 and 2020 labour migration. A Multidirectional Optimum Ecotope Base Algorithm (AMOEBA) dihitung menggunakan Local Indicators of Spatial Association (LISA).

The Global Moran's Index use to analyze the presence or absence of spatial autocorrelation in the data. Global Moran's I is used to identify the existence of spatial interactions for all observations. the global Moran index range with the standardized spatial weight matrix is $-1 \leq I \leq 1$. A value of $-1 \leq I \leq 0$ indicates a negative spatial autocorrelation, while $0 \leq I \leq 1$ indicates a positive spatial autocorrelation.

Table 7 shows the results of Global Moran's I calculations of the workforce of Central Java Province with a negative pattern of -0.09 and insignificant from 2014 to April 2020. The interaction pattern of Central Java Province

workforce spreads from one district or city to district or city another. The results of the p-value calculation with a significant level of $\square = 5\%$ indicate that the overall pattern of energy spatial interactions from 2014 to April 2020 is not significant.

Table 7. Global Moran's I Labour

Years	I	P-value
2014	-0,029	0,422
2015	-0,029	0,445
2016	-0,029	0,433
2017	-0,029	0,394
2018	-0,029	0,402
2019	-0,029	0,419
2020	-0,029	0,419

Source: Processed Data Using Stata, 2021

Table 7 shows negative Global Moran's Index value from 2014 to 2020, which is all the same, namely -0.029, meaning that the 29 regencies and six cities observed do not have the same workforce characteristics as their neighbouring regions. Table 4 shows that the

Global Moran's Index value is not significant from 2014 to 2020. This indicates that there is no pattern of spatial interaction (within in-group) both similar and dissimilar to the characteristics of the workforce.

This study uses a level of confidence with a significance level $\alpha = 5\%$. The value of the Global Moran's Index significantly identifies the existence of patterns of spatial interactions (within in group), both similar and dissimilar. Pattern + indicates the presence of convergence or clusters, Pattern - indicates distribution or diverging. The value of Global Moran's Index is not significant, identifying the absence of similar or dissimilar patterns of spatial interactions within in group.

Table 7 shows that the Global Moran index value of the workforce from 2014 to 2020 is negative, meaning that it identifies a spatial interaction pattern that is spread or divergent. This study uses a significance level of =5%. The Global Moran Index value of labor is smaller than P_value, which indicates that the spatial interaction pattern of the workforce is random because there is no clear feature pattern. The Global Moran index value of labor identifies the existence of spatial patterns (with in groups) both similar and dissimilar, meaning that it is suspected that the global spatial interaction pattern has similar characteristics of the workforce, or geographical proximity of the distances between regions. This study uses a spatial weight matrix of Euclidean Distance to solve problems related to the distance between regions, problems of distance between regions, problems of transportation modes between regions, and problems of labor mobility between regions. The Euclidean Distance spatial weight matrix uses the X coordinates and Y coordinates of an entity.

The research results support this by Caroline et al. (2018). Global Moran's Labour Index of 10 ASEAN countries from 2004 to 2011 shows converging or clustered labour spatial interactions. However, the spatial interaction pattern of the workforce of 10 ASEAN countries from 2012 to 2015 shows a pattern of spatial interaction that is spread or divergent. The value of the Global Moran's Index from 2004 to 2011 was significant at = 5%, indicating a spatial

interaction pattern. Meanwhile, the Global Moran's Index value from 2012 to 2015 identified the absence of similar or dissimilar spatial interaction pattern (within in-group).

Table 7 shows the strong change in the spatial interaction pattern of the Workers in Central Java Province. Initially, in 2014, there were 11 Regencies and one city (Cilacap Regency, Demak Regency, Banjarnegara Regency, Banyumas Regency, Jepara Regency, Kebumen Regency, Pati Regency, Semarang City, Pemalang Regency, Tegal Regency, Temanggung Regency, Semarang Regency) with the characteristics of Labor tall one. They interact spatially with districts and cities with high workforce characteristics. The practice of spatial interaction of the workforce changed in April 2020 to 5 sections (Cilacap Regency, Banyumas Regency, Batang Regency, Blora Regency, Blora Regency) with high labour characteristics that interact spatially with districts and cities with high labor characteristics. This study focuses on the solid spatial interaction patterns of labour between districts and cities in Central Java.

Changes in the solid spatial interaction patterns of the workforce are thought to be influenced by the "Barlingmaskeb" strategic area system: Banjarnegara Regency, Purbalingga Regency, Banyumas Regency, Cilacap Regency and Kebumen Regency. The strategic area system of Blora Regency and Rembang Regency is included in the "Banglor" which is headquartered in Cepu. Batang Regency is a strategic area "Petanglong" which consists of Pekalongan Regency, Batang Regency, and Pekalongan City. Barlingmaskeb, Banglor, and Petanglong were formed based on regional authority to create cooperation between regions with geographic characteristics and limited areas to meet their needs.

Changes in labour interaction patterns in 2020 are thought to have occurred because of the COVID-19 pandemic in March 2020 in Central Java Province, namely 55,803 Cilacap Regency, with 1,355 COVID-19 cases, Demak Regency with a total of 2,322 COVID-19 cases. Banjarnegara Regency with a total of 721 COVID-19 cases, Banyumas Regency with 1,371 COVID-19 cases, Jepara Regency with 2,524 COVID-19 cases, Kebumen Regency with 2,366

COVID-19 cases, Pati Regency with a total of 2,366 people. There are 1,098 COVID-19 cases, Pemalang Regency with 1,364 COVID-19 cases, Tegal Regency with 1,406 COVID-19 cases, Temanggung Regency with 1,477 COVID-19 cases, Semarang Regency with 1,629 COVID-19 cases. Semarang City with a total of 8,733 COVID-19 cases. The impact of covid occurred on the workforce of Central Java Province in 2020.

Table 8 shows that there are 20.33 percent of workers affected by COVID-19 in Central Java Province who have been laid off, 68.69 percent of workers have been laid off, 10.98 percent of the informal sector has been affected by COVID-19.

Table 8. Workers in Central Java Province Affected by Covid in 2020

workers affected by covid 19	May 2020
Work termination	47,266
	20.33%
Workers laid off	15,9691
	68.69%
Informal sector workers	25,518
	10.98%
Total	**232,475**

Source: Ministry of Labour 2020

Cilacap Regency has leading sectors: the manufacturing industry, the trade sector, hotels and restaurants. Banyumas Regency has leading sectors: the plantation sub-sector, the excavation sub-sector, the electricity sub-sector, the clean water sub-sector, and the building rental sub-sector. Rembang Regency has a leading sector, namely the manufacturing sector, the electricity, gas and clean water sector, the financial sector, leasing, corporate services. Blora Regency has leading sector: the manufacturing sector, the electricity, gas and clean water sector, the building sector, and the services sector. Batang Regency has leading sectors: the agricultural sector, the mining sector and the manufacturing sector. Changes in the spatial interaction pattern of labour in 2014 and April 2020 are thought to be due to workers who work as labourers, and employees in 2020, amounting to 39.78% or 5,979,731 workers.

**Figure 4.** Number of Workers Based on Employment Status in 2020.
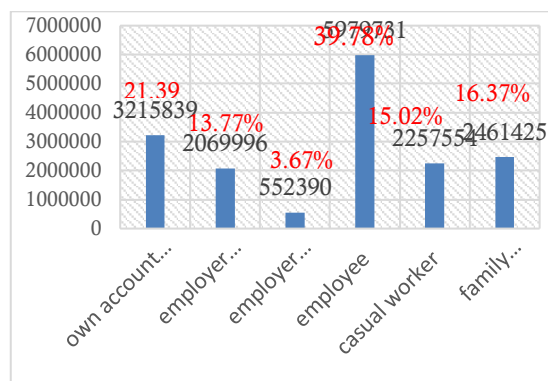
Source: Central Java in Figures, 2021

Figure 4 shows that most workers work as labourers, and employees, followed by workers with self-employment status 21.39%. Workers who work as employees are suspected of migrating labour to obtain higher income from their area of origin. The workforce thinks realistically to seek a decent level of welfare and living.

Changes in the spatial interaction pattern of workers are thought to be due to workers with low levels of education. Workers look for work according to the needs and level of expertise that the workforce has. Workers will travel to other area that are closer to the place where they work. Figure 5 shows the force with high work mobility, primarily senior high school education, 38%, followed by workers with elementary school education 23%, workers with junior high school education 20%.

Figure 5. Workforce based on Education Level in 2020
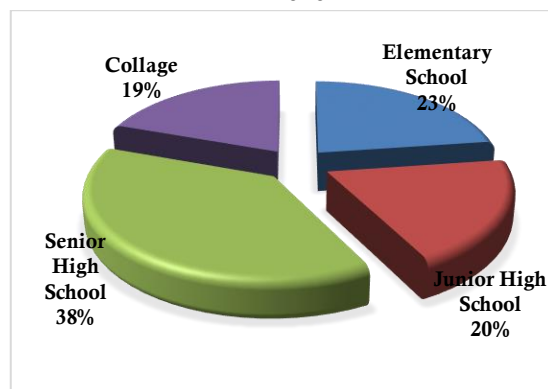
Source: Central Java in Figures, 2021

Changes in the spatial interaction pattern of workers are thought to be due to differences in the minimum wage of workers, thus making the reason for workers to move to other areas to seek the welfare and income differences. Figure 4 shows the difference in wages received by workers. Semarang City's highest labour wage is 2.8 million, followed by Demak Regency 2.5 million, Semarang Regency 2.3 million, Cilacap Regency 2.2 million, Batang Regency 2.1 million, Banyumas Regency 1.97 million, Pati Regency 1.95 million, Blora Regency 1.89 million, Rembang Regency 1.86 million, and Banjarnegara Regency 1.8 million.

Figure 6. The 2020 Minimum Wage Difference
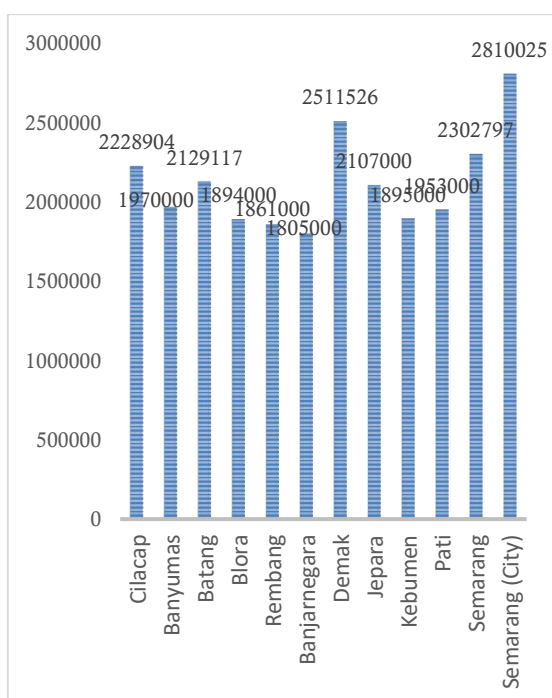
Source: Central Java in Figures, 2021

Changes in labour interaction patterns are thought to be due to the absorption of different employment opportunities for each sector in 2020. Figure 6 shows that Banyumas Regency absorbs a lot of workers in the tertiary sector 397,006; Cilacap Regency absorbs a lot of workforce in the tertiary sector 321,005; Batang Regency absorbs many workers in the tertiary sector 195,192; Blora Regency absorbs a lot of workforce in the primary sector 222,373; Rembang Regency absorbs a lot of workers in the primary sector 123,885.

Figure 7. Labor by Sector
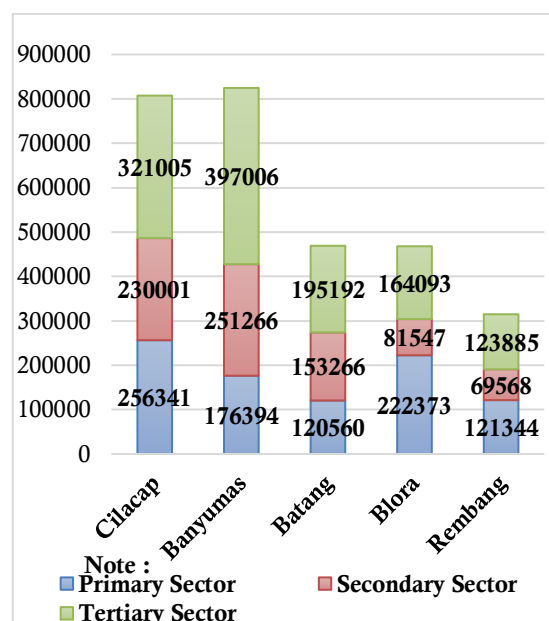
Source: Central Java in Figures, 2021

The primary sector consists of agriculture, forestry, and fishing. The secondary sector consists of mining and quarrying; manufacturing; electricity and gas; water supply; sewerage, waste management, and remediation activities, construction. The tertiary sector consists of wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage; accommodation and food; service activities; information and communication; financial and insurance activities; real estate activities; business activities; public administration and defence; compulsory social security; education; human health and social work activities; other services activities.

The strong spatial interaction pattern of the workforce in 2014, there were 11 regencies, and one city to only five regencies in April 2020, allegedly due to policies related to the Covid-19 pandemic with restrictions on community social activities, social distancing, and the "5 M" government program, namely wear a mask, wash hands, wear hand sanitiser, stay away from the crowd and reduce mobility. All government policies related to the Covid-19 have been many impacts on the economic growth activities of Central Java Province through a decrease in the level of productivity of workers whose health has been affected due to exposure to Covid-19. This

research is supported by the results of research from Kickbusch et.al. (2020), and Nicola (2020). Research results from Kickbusch et.al. (2020) it is known that the covid pandemic has a negative impact on human health, welfare, economic growth. This is reinforced by the results of research from Nicola (2020) that the policy of limiting regional economic activities as a result of the impact of the covid pandemic has caused a decline in all economic sectors.

The impact of covid 19 is seen in the policy of limiting working hours in Central Java Province. Several responses from companies regarding the policy of limiting working hours in Central Java Province obtained from the survey results from the Central Statistics Agency from July 10, 2020 to July 26, 2020 on 3,082 business actors affected by COVID-19, show that there are 27 percent of companies that are still operating such as normal but there is a reduction in the working hours of their employees, there are 12 percent of companies implementing work from home by terminating their workers or the company's unpaid workers, 15 percent of companies operating more than their working hours capacity, 36 percent reducing their working hours, 17 percent not to pay their workers, there are 11 percent of companies that stop workers. This happened in the construction sector, 26 percent of which had terminated their workforce, 18 percent of the manufacturing industry had terminated their workforce, the accommodation sector, and the food and drink sector had 14 percent of their workforce.

Central Java province workers affected by COVID-19 on 27 May 2020 totalled 232,471 workers with details: there were 47,266 workers laid off, 159,691 workers were laid off, and there were 25,518 informal workers (Ministry of Manpower, 2020).The change in spatial interaction pattern Central Java workforce in 2020 is thought to be the result of the impact of COVID-19 on the force. This research is supported by the results of Krisna Adhi Pradipta's study (2020) that the workforce affected by covid 19 is a workforce with a high school education level (SMA) of 52 per cent, workers affected by covid 19 with a Diploma IV level and a bachelor's degree are 30. Per cent, the

workforce involved by COVID-19 with a Diploma education level is 11 per cent.

This research is supported by several research results, including qualitative research from Ogunlela and Tengeh (2020) which examines the impact of covid 19 on immigrant workers. The results of Ogunlela and Tengeh's qualitative research (2020) on the impact of covid 19 on immigrant retail business in South Africa, it is known that the South African government's policy of limiting economic activities due to the covid pandemic does not support immigrant retail business activities.

The results of the research by Webb et.al., (2020) note that the government's policy regarding COVID does not support workers in the informal sector related to the absence of a safety policy for informal sector workers, and guaranteed income for informal sector workers. Many of the informal workers in the economic sector do not receive financial support from the government (Williams and Kayaoglu, 2020). The results of the research from Papoutsaki and Wilson (2020) showed that the impact of covid 19 on the economic sector that occurred in the UK was mostly in sectors that employed young workers, women, minority groups, and certain ethnic groups.

Research from Chen & Hong (2020) found that the impact of COVID-19 on private companies in China was to significantly cut wages, delay salaries, and stop paying employees. The impact of Covid is also felt in the agricultural sector, the tourism sector. The research of Bochtis et.al., (2020) on the impact of covid 19 on the agricultural sector in the United States in 2020. The results of the research of Bochtis et.al., (2020) it is known that there are 50% of the workforce in the agricultural sector affected by the impact of covid 19 which brings the continued impact of the decline in labor income in the agricultural sector to 54%.

Research results from Ranald (2020) note that the impact of covid 19 at the beginning of the first quarter of 2020 caused a decrease in trade in goods minus 3 percent from the first quarter of 2019. The decline in trade in the second quarter of 2020 was minus 13 percent occurred in the transportation, tourism, education sectors , trade.

Research Agrawal, Jamwal et. al., (2020) on the impact of covid 19 in Greece, Portugal, and Spain. The results of research from Agrawal, Jamwal et. al., (2020) it is known that the countries of Greece, Portugal, and Spain that depend on the tourism sector are affected by the impact of covid 19 through a significant impact on the market, industry and global economic growth of Asia.

An empirical study of the impact of covid 19 on airport workers has also been carried out by Simhan (2020) it is known that there are 35,000 agents and workers who are not paid and leave work due to the impact of covid 19 on the aviation sector at Indian airports. The impact of covid 19 on the workforce through technological transformation has been studied by Savic (2020). The results of research from Savic (2020) it is known that the impact of covid 19 causes a technological transformation. Initially, the workforce worked in the office, but since the COVID-19 pandemic, working at home has become a mandatory requirement. The sudden need to work from home is bringing about a digital transformation of the workforce through online video conferencing, online purchasing, custom delivery, telemedicine, e-learning, e-commerce, online marketing, video streaming.

In contrast to previous researchers. Eikhof's research (2020) takes a cultural approach to the impact of covid on the economic sector. Research results from Eikhof (2020) show that the impact of covid 19 on the cultural economy poses a threat to the cultural diversity of the workforce. This is indicated by the different abilities of the workforce in supporting short-term income insecurity.

UNCTAD (United Nations Conference on Trade and Development) in 2020 announced that the impact of COVID-19 had an impact on public health, breaking the chain of people's movement, and causing serious macroeconomic problems.

The results of Barua's research (2020) note that the impact of covid 19 on the macro economy causes public distrust, loss of buyer confidence, loss of seller confidence, so that aggressive policies, innovative policies in the long term are needed.

The results of research by Fornaro and Wolf (2020) show that the COVID-19 pandemic caused a decline in aggregate supply in China, down 35.7 percent in February 2020. Fernandes (2020) predicts that GDP growth due to the impact of COVID-19 will decline between 3 percent and 5 percent depending on the conditions of each country. China's economic growth in the first quarter of 2020 fell between 3.5% to 4 percent (Mishra, Gupta et. al., 2020).

The results of research from Ozili and Arun (2020) found that an increase in the number of restrictions on social activities, monetary policy decisions, international travel restriction policies greatly affects the level of economic activity, and helps determine the highest or lowest index of the stock market. On the other hand, the coercion of internal activities and policies to increase spending on monetary activities will have a positive impact on economic activity. The Corona virus case did not have a significant impact on economic activity.

CONCLUSION

The change in the strong spatial interaction pattern of the workforce from 2014, which consisted of 11 regencies and one city to 5 regencies in April 2020, is suspected because there are several reasons, among others, suspected because: first, Cilacap Regency, Banyumas Regency, Blora Regency. Rembang Regency is included in the strategic area "Barlingmaskeb". Batang Regency is a strategic area "Banglor". Batang Regency is included in the strategic area "Petanglong". National strategic areas are formed based on regional authority to form cooperation between regions with geographic characteristics and limited areas to meet their needs. Second, it is suspected that Cilacap Regency, Banyumas Regency, Batang Regency, Blora Regency and Rembang Regency have superior sectors which are national development priorities. Third, most of the workforce who carried out mobility to other areas worked as laborers, employees and employees in 2020 as many as 39.78% or 5,979,731 workers. Fourth, the difference in the minimum wage for workers is the reason why workers move to other areas in search of welfare and income differences.

Fifth, the change in labor interaction patterns is thought to be due to the absorption of different jobs for each sector in 2020. This is evidenced by the presence of Banyumas Regency, many Cilacap Districts, Batang Regency which absorbs a lot of workers in the tertiary sector. Blora Regency and Rembang Regency absorb a lot of workers in the primary sector. Sixth, allegedly due to the Covid-19 policy with restrictions on community social activities, social distancing, and the "5 M" government program, namely wearing masks, washing hands, wearing hand sanitisers, staying away from crowds and reducing mobility. With the existence of all government policies related to the existence of Covid-19, there are many impacts on the economic growth activities of Central Java Province through a decrease in the level of productivity of workers whose health is disrupted due to exposure to Covid-19.

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