Network Characterization of Goods Movement in Indonesia

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Abstract. Network characterization of goods movement is particularly important to estimate needs and accurate management for freight transportation. The present study aims at characterizing the network of goods movement in Indonesia and examining the effectiveness of network characterization for prediction purpose. A network approach using RStudio was applied. It was found that the network of goods movement in Indonesia is characterized by weak inter-provincial goods movement, scale-free network, disassortative, having rich-club phenomenon, and having a core-periphery structure in which Sumatera Barat (West Sumatera) and Jawa Barat (West Java) appears to be the cores of the network. The findings also demonstrate that the prediction model developed by characterization performs better and can explain, on average, 39% of the variances. The prediction models for chemicals, fuel, meat and livestock, fish, crude oil, and fertilizer, have even better capability to explain variances in the volumes of goods movement by more than 60%. Potential avenues for future research are also discussed.

1. Introduction

Based on a survey of the Logistic Performance Index (LPI) conducted by the World Bank in 2018, Indonesia has been ranked 51 out of 167 countries being examined, which is corresponding to 3.08 out of 5.00 scale [1]. Among the ASEAN countries, Indonesia is still inferior to the performance of Singapore (5th), Thailand (34th), Malaysia (35th), and Vietnam (45th). Among the six aspects to be evaluated for the LPI, customs and infrastructure are two components that have the lowest score, corresponding to 2.69 and 2.81 respectively. Meanwhile, international shipments, tracking and tracing, logistics competence, and timeliness are recorded above the score of 3. Despite, the LPI improvement, logistics cost in Indonesia remains high, accounting for 24% of the Indonesian GDP, whereas Thailand and Malaysia have logistics cost as much as 15% and 13% of GDP, respectively. 72% percent of the Indonesian logistics cost is attributable to transportation [1].

Reducing logistics can, therefore, improve the performance of the logistics system and, consequently, improve industrial competitiveness. Given that transportation cost seems to be the most contributor to logistics cost, understanding the logistics activities such as goods movement contributing to the logistics cost is of importance. The present study aims therefore at characterizing the network of goods movement in Indonesia and examining the effectiveness of network characterization for prediction purpose. It is expected that by understanding the network of goods movement, the needs of freight transportation can be appropriately mapped, thus accurate and effective management can be designed.
The present study is based on the empirical data from a survey conducted by Badan Penelitian dan Pengembangan Kementrian Perhubungan (Transportation Research and Development Agency). The survey recorded the volume of goods movement from one province to another province. The survey was intended to support the design of transportation policies including investment, operation, management and regulatory, in order to improve transportation facilities/infrastructure and to improve transportation operation to be smoother, timely, low-cost, safe and comfortable, environmentally friendly, energy-efficient, and having lower levels of goods breakage.

Existing literature on goods movement has attempted to build a model to estimate the goods movement and analyze the causal relationships between explanatory variables and the movement. For instance, [2] identified influential variables on the goods movement using regression methods and neural network. The most recent approach, i.e., network analysis has received more attention in characterizing the network of goods based on the goods movement itself. The network analysis is able to explain the goods movement based on inter-regional relations. [3] had implemented a network approach to estimate the connectedness of commodity using a network approach. Moreover, the network approach has also been common to be used to analyze international trade networks such as [4]. On the other hand, existing studies to explore goods movement in Indonesia using a network approach is still rare.

The present study has therefore contributed in three ways. First, the present study demonstrates the implementation of the network approach to characterize goods movement based on the empirical freight survey for 33 goods categories, which is the novelty of the present research. Second, based on the network analysis, the study provides insights into the characterization of the goods movement network in Indonesia. Third, the study has also contributed theoretically to demonstrate the effectiveness of network characterization for prediction purpose.

The paper is structured as follows. This section has highlighted the motivation of the study. Section Two provides a brief review of existing literature on goods movement and the network approach. Section Three describes the methodology of the network approach fitted to the needs of the study, which is followed by the results and discussion in Section Four. Section Five concludes the overall findings of the study and suggests potential avenues for future research.

2. Literature Review

The section is divided into two parts. The first part deals with a brief review of existing literature on goods movement. The second part describes network characterization to provide sufficient theoretical background of the research.

2.1. Literature on Goods Movement

Literature investigating goods movement has existed. Regression, Artificial Neural Network, and the combination of both approaches are among the approaches used in predicting goods movement. Using regression and based on US Commodity Flow Survey (CFS), [5] aimed to investigate the correlation between origin and destination and its effect on the spatial interaction model/network. The study found that the correlation between origin and destination should be taken into account when modeling the inter-regional goods movement. [6] contrasted Artificial Neural Network (ANN) approach and regression in predicting goods movement based on Thailand CFS. The study was found that ANN provided better results in making the prediction. Meanwhile, based on the US Commodity Flow Survey (CFS), [2] has estimated the goods distribution using the Artificial Neural Network approach. The study used variables in the gravity model as independent variables, while the value of goods in units of USD (US dollars) is a dependent variable. However, ANN has a weakness in the form of a black-box phenomenon and inflexibility toward network changes. This phenomenon makes ANN fail to establish a causal relationship between the variables that make up the system which makes it difficult to determine influential variables. Based on these weaknesses, ANN should be combined with
Another approach has been used in understanding goods movements such as gravity model. [7] estimated regional transport demand using South Korea's CFS data using Four-Step Travel Original-Destination Estimation as well as the gravity model. Based on data on production, consumption, the volume of goods movement, transportation, the flow of transport in the metropolitan area can be estimated. It was found that the commodity-based method between regions may not be appropriate to estimate goods flow in a metropolitan area.

The most recent approach, i.e., the network approach, has received increasing attention to investigate goods movement. For instance, [4] analyzed international trade networks. The study demonstrated that the relationship of the network is weak, disassortative, and countries with intensive trades will tend to group with those of similar. Other research on international trade networks was conducted by [8] who investigated rare commodities in the world. The results show that international rare commodity networks display scale-free characteristics from 1996 to 2015. The distribution of kernel density is significantly skewed to the right, which indicates that most countries have few trade partners, while only a few countries have many trading partners. Besides, the communities formed in the trade of rare commodities in the world show a tendency towards integration. [3] has identified the connectedness of 18 commodity futures and illustrated that agricultural futures are vulnerable to shocks, whereas metal futures are net transmitters of shocks to others. The results of this study are able to provide insights into the connectedness of the commodity network so that forewarned could be issued when a turmoil of commodity exists.

The present paper, therefore, opts to network approach as the approach is suitable to characterize the goods movement network in Indonesia so that it could be useful to estimate transportation needs, and consequently better transportation design and policies.

2.2. Network Characterization

Understanding goods generation and goods movement are crucial for analyzing national transport demand, estimating future goods movement, and apparently, designing transportation-related policy [9]. It appears that the network approach is a promising tool to analyze the goods movement. As the network has specific topological features, characterization of the network is necessary to identify the features which then influence the dynamics of activities that occurred on the network.

According to [10], network characterization is divided into two parts, i.e. nodes-edges characterization and cohesiveness characterization. Nodes and edges are the main elements where the nodes-edges characteristics are determined. The characteristics depend on the role of nodes which is based on the outgoing and incoming edges. When it comes to cohesiveness characterization, there are many ways to define depending on the research context. Network cohesiveness indicates the tendency of relationships between nodes.

When it comes to network characterization, there are several network parameters, i.e., connectivity, assortativity, clustering, and centrality [11], which are used in the present study. Connectivity is used to find out relations between provinces. The analysis was carried out by identifying the distribution of Node Degree (ND) to find out which provinces are more connected with other provinces and vice-versa, and by identifying the distribution of Node Strength (NS) to determine the intensity of the relationship based on goods movement. The evaluation of the distribution based on Kernel density estimation, a non-parametric statistical method for estimating the probability of density functions of random variables introduced by [12-13], was carried out. Furthermore, the shape of the distribution is analyzed based on skewness and kurtosis. Besides, distributions of ND and NS have evaluated whether or not the distributions follow power-law distributions. The power-law distribution introduced by [14], the most popular distribution, can be categorized as the topology of the scale-free network. Node degree (ND) and Node Strength (NS) only provide the relationship but not how the relationship formed. Assortativity indicating the province's tendency to form relationships with other provinces the first indicator is, therefore, the second parameter to characterize the network. Assortativity examines
the compatibility of provinces making a relationship concerning goods movement. The correlation between the Average Nearest Neighbor Strength (ANNS) with NS will produce assortativity values ranging from -1 to +1. A negative value indicates that the network is disassortative which means a province with high NS will tend to relate to a province with low NS value, while a positive value indicates that the network is assortative, meaning a province with a high NS will tend to relate to a province with high NS as well. The third parameter of network characterization is clustering. Clustering patterns are identified based on the behavior of the province forming triangular connections with other provinces, or in other words, it evaluates whether a province tends to relate to provinces from the provinces that are connected with it. The parameter considered in this indicator is the Clustering Coefficient (CC). The correlation between CC and NS of the network which indicates the tendency of the province to form a group is therefore analyzed. The three previous parameters of network characterization focus on the relationship among the provinces, how the provinces are connected, and forming groups. However, the fourth parameter, centrality determines which province(s) is(are) the core of the network – the most important and influential provinces in the goods movement network. Eigenvector was used to evaluate the centrality. Province(s) with high centrality is considered as the most important province(s) in the network as the province(s) is(are) connected with other important provinces.

3. Methodology
To characterize the network of goods movement, the network approach is utilized. Goods are categorized into 33 groups, as shown in Table 1. Goods movement is aggregated by analyzing the movements between provinces which is represented as links/edges, and each province is a node that is connected by the links to other nodes. Connectivity, assortativity, clustering, and centrality are used as parameters to characterize the network.

| No | Goods                         | Code | No | Goods                         | Code |
|----|-------------------------------|------|----|-------------------------------|------|
| 1  | Chemicals                     | Chem | 18 | Sugar                         | Sugar|
| 2  | Coal                          | Coal | 19 | Fish                          | Fish |
| 3  | Fuel oil                      | Fuel | 20 | Rubber                        | Rubb |
| 4  | Rice                          | Rice | 21 | Logs                          | Logs |
| 5  | Iron steel                    | IronS| 22 | Processed Timber and forest products | Timb|
| 6  | Seeds (others)                | SeedO| 23 | Two-wheel vehicle             | 2Veh |
| 7  | Seeds for Farming             | SeedF| 24 | Four-wheel vehicle            | 4Veh |
| 8  | Iron ore                      | IronO| 25 | Coffee                        | Coffe|
| 9  | Fruit                         | Fruit| 26 | Cooking oil                   | CookO|
| 10 | Crude Palm Oil                | CPO  | 27 | Crude oil                     | CrudeO|
| 11 | Meat and livestock            | Meat | 28 | Fertilizer                    | Fertil|
| 12 | Electronics for household     | El-Hou| 29 | Vegetables                    | Vege |
| 13 | Electronics for communication | El-Com| 30 | Cement                        | Cent |
| 14 | Salt                          | Salt | 31 | Spare parts                   | SparP|
| 15 | Natural gas                   | NatG | 32 | Mining (Other)                | MinO |
| 16 | General cargo – Food          | Food | 33 | Textile                       | Textl|
| 17 | General cargo – Non-Food      | Non-Food | |

Data on the goods movement was obtained from the national survey of origin-destination (so-called ATTN = Asal Tujuan Transportasi Nasional) which was conducted by Badan Penelitian dan Pengembangan Kementrian Perhubungan (Transportation Research and Development Agency). Other
supporting data such as Gross Domestic Product (GDP), population data, and geographical coordinates of provincial capitals were also collected.

RStudio was used for network analysis. The main R package of igraph was used for characterizing the goods movement network and that of the random forest was used for predicting the good movements. When it comes to prediction analysis, two models were developed and contrasted. The first prediction model was developed using a simple gravity model which was commonly used for predicting goods movement. The second prediction model was developed using network parameters that were obtained from the network characterization. The motivation of using the random forest is the capability of accommodating data with a large number of independent variables and of determining the independent variables important in the prediction.

4. Results and Discussion
Following the objectives, the section is divided into two parts, i.e., network characterization and the evaluation of the effectiveness of network characterization for prediction purposes.

4.1. Network Characterization
Total volume of aggregate goods movement is 1,097,316,703 tons/month. Goods which is accounting for the highest proportion is coal with a total volume of 764,098,394 tons/month, corresponding 69.63% of the total goods movement, whereas mining (other) contributes to the least, accounting for 0.04% of the total goods movement. The basic structural network is presented in Table 2.

| No  | Parameters                | Value |
|-----|---------------------------|-------|
| 1   | Connected node            | 33    |
| 2   | Number of edges           | 1056  |
| 3   | Density                   | 0.94  |
| 4   | Percentage of mutual edge | 100%  |
| 5   | Average path length       | 1     |

The network density of 0.94 which is close to 1 indicated that almost all provinces in Indonesia are well-connected, however, Papua Barat province is the only province that is yet not connected. The percentage of the mutual edge of 100% means that the good movement among provinces is reciprocal. High network density and the high percentage of a mutual edge corresponds to relatively low average path length, implying that the goods movement is point-to-point, the goods movement from one province to another province does not require the presence of a mediator. In order to detail the network characterization, the analysis of network characterization based on the aforementioned parameters, i.e., connectivity, assortativity, clustering, and centrality is detailed as the following.

Connectivity
Connectivity corresponds to the relative degree of connectedness among provinces which were measured by node degree and node strength as shown in Table 3. Based on ND and NS, distribution analysis for both ND and NS was conducted. It appears that the ND distribution tends to be left-skewed with a peak of more than 30 for ND-in and ND-out and more than 60 for ND-total. It implies that that most of the provinces have been connected with almost all other provinces, while only a small number of provinces are connected with a few others. On the contrary, it appears that the NS distribution is right-skewed with a peak range of 0 – 0.2. The difference between the ND and NS distribution shows that the goods movement between provinces is dominated by weak relationships, only a few provinces that have a strong relationship. The correlation between ND and NS distribution is then analyzed using Pearson Correlation to identify the relationship between the movement and movement. A low positive correlation indicates the movement relating to the intensity (weight of goods) is weak.
Table 3. Node Degree (ND), Node Strength (NS), and Correlation Coefficient

| No | Parameters | Means  | SD   | No | Parameters | Means  | SD   |
|----|------------|--------|------|----|------------|--------|------|
| 1  | ND-in      | 31.06  | 5.49 | 4  | NS-in      | 0.12   | 0.24 |
| 2  | ND-out     | 32.03  | 5.66 | 5  | NS-out     | 0.12   | 0.29 |
| 3  | ND-total   | 64.06  | 11.32| 6  | NS-total   | 0.25   | 0.38 |

Further analysis using the Kolmogorov Smirnov test as shown in Table 4 was then conducted to identify whether or not the network can be classified as a scale-free network. A network can be categorized as a scale-free network if the strength of the network follows the power-law distribution. Based on the result, it can be concluded that the network follows the scale-free network. As the scale-free network follows preferential attachment, it further implies that when there is a new goods movement, the movement is likely to occur in the provinces with high Node-Strength (NS).

Table 4. Results of power-law distribution fit

| No | Parameters | KS statistics | p-value |
|----|------------|---------------|---------|
| 1  | NS-in      | 0.11          | 0.62    |
| 2  | NS-out     | 0.14          | 0.52    |
| 3  | NS-total   | 0.11          | 0.36    |

Assortativity

Assortativity represents to what extent the provinces associate with other provinces in the network, being of similar sort or being of opposing sort. It is usually determined for the degree (number of direct neighbors) of the province in the network. The study uses Average Nearest Neighbor Strength (ANNS) and the ANNS results are presented in Table 5. Similar means and standard deviation of ANNS indicates that the provinces have the same partners in sending goods and receiving goods. Besides, this is supported by the percentage of the mutual edge of 100% which causes all movements that occur between provinces to have reciprocal relations.

Table 5. Average Nearest Neighbor Strength (ANNS) and Correlation Coefficient

| No | Parameters | Means  | SD   | No | Parameters | Means  | SD   |
|----|------------|--------|------|----|------------|--------|------|
| 1  | ANNS in-in | 0.12   | 0.02 | 4  | ANNS out-out | 0.12   | 0.02 |
| 2  | ANNS in-out| 0.12   | 0.02 | 5  | ANNS total  | 0.49   | 0.09 |
| 3  | ANNS out-in| 0.12   | 0.02 |     |             |        |      |

The correlation analysis between ANNS and NS values was then performed using Pearson Correlation to determine the relationship of the goods movement and how provinces determine partners. It appears that the network shows a weak disassortative property. It indicates that provinces that have high connectivity (high NS values) will tend to carry out goods movement activities with provinces that have low connectivity (low NS values). The positive small correlation between ANNS in-out and NS-in and ANNS out-in and NS-out indicates that sending and receiving as well as receiving and sending do not affect each other's relations between provinces in determining partners. It appears that the receipt of goods, the recipient province is not influenced by the number of goods
moving out (NS-out) from the partner province. Likewise, in sending goods, the sending province is not affected by the number of incoming goods (NS-in) from partner provinces. The negative correlation indicates that the network disassortative. It appears that if a province has sent goods to another province, then the sending province tends to have low shipping connectivity (low NS-out). Similarly, if the province has received goods from another province, then the recipient province tends to have low connectivity (NS-in).

Clustering

Clustering Coefficient (CC) is normally used for clustering evaluation which represents the degree to which a province tends to cluster/group. Table 6 shows the CC of the network. the average CC value is relatively small and even close to zero. This shows that the provinces have a low frequency in forming clusters particularly the cycle type of triangles as indicated by the lowest CC. The small value of CC indicates that the network is weakly clustered.

Table 6. Clustering Coefficient

| No | Parameters | Means   | SD     |
|----|------------|---------|--------|
| 1  | CC-cycle   | 0.00089 | 0.00069|
| 2  | CC-middleman| 0.00109 | 0.00086|
| 3  | CC-in      | 0.00109 | 0.00100|
| 4  | CC-out     | 0.00109 | 0.00117|

Further correlation analysis between was CC-total dan NS-total was conducted and resulted in a positive relationship of 0.78. It means that that a province with a high goods movement has a high level of interconnection of the triangle, making it easy to group with other provinces. The positive and high correlation value also indicates that the network has a "rich club phenomenon". In other words, the provinces with high goods movement tend to group with other provinces with high goods movement. This phenomenon is also in line with the theory of [15], so-called "strength of strong ties", where there is a core-periphery structure, indicating that the network has provinces that act as hubs and other provinces act as supporters or peripherals.

Centrality

Centrality indicates the most important provinces within the network. Using eigenvector centrality, the centrality of the network, i.e., the province with the highest centrality, which is connected with other high centrality provinces, was assessed. Figure 1 shows the centrality distribution of the provinces in which the x-axis represents eigenvector centrality, while the y-axis is the density or frequency of occurrence of the eigenvector centrality value. The figure shows that the graph is right-skewed and thin-shape, which indicates only a few provinces which have high centrality. The result is in line with the previous findings demonstrating that the network performs a core-periphery structure.

Figure 1. Kernel density eigenvector centrality
The existence of the core-periphery structure in the network implies that some provinces have a role as a core/hub and others are periphery or support. The number of hubs in the network was determined using the 95th percentile following [4]. It appears that only 5% of provinces with the highest centrality value or the two largest, i.e., Sumatera Barat (West Sumatera) and Jawa Barat (East Java) are hubs. It can be justified that West Sumatra is a coal-producing province and coal movement accounts for the highest proportion of 69.63%. On the other hand, Jawa Barat has almost all goods movement on the list (Table 1). As both Sumatera Barat and Jawa Barat appears to be the hubs, it implies that changes in conditions and policies in both provinces would significantly influence the structure of the network.

4.2. Effectiveness of Network Characterization for Prediction Purpose

This sub-section aims at examining the effectiveness of network characterization for network prediction purpose. The prediction model is developed to estimate the volume of goods moving from one province to another. The prediction analysis would be useful for estimating the needs for freight transportation.

Two prediction models are therefore developed. The first prediction model (Model 1) is, to be used as a comparison model, built with independent variables using simple gravity model parameters which are often used to predict the movement of goods. The parameters include Gross Domestic Product (GDP) per capita of origin province, GDP of destination province, the total population of origin province, the total population of destination province, and distance between provinces. The second prediction model (Model 2) is the main model to be developed based on the parameters obtained from the aforementioned characterization, i.e., ND-in, ND-out, ND-total, NS-in, NS-out, NS-total, ANNS in-in, ANNS in-out, ANNS out-in, ANNS out-out, ANNS total, CC cycle, CC middleman, CC in, CC out, CC total and eigenvalue. The parameters are divided into three variable groups including the origin variable (sender), the destination variable (receiver), and the similarity variable. The origin variable is the network parameters in the origin province, the destination variable is the network parameters in the destination province, and the similarity variable is the similarity of the network parameters of the origin province and the destination province. The similarity variables were calculated based on [16], i.e., by multiplying the parameters of the province of origin with the parameters of the province of destination. The method was based on the principle of preferential attachment. The dependent variable of the two prediction models is the volume of goods movement between provinces.

The available data of goods movement was divided into two parts, i.e., training data and testing data with a ratio of 70:30. Training data is used to build the model, while testing data is used to validate the prediction model. The available data is divided into two parts randomly.

The performance of the developed prediction models is measured by percent variance explained which explicates the variances of the dependent variable is explained by independent variables, as shown in Figure 2. The figure shows that the prediction model based on network characterization performs better.
The average percent variance explained is 30% and 39% for the first prediction model and the second prediction model respectively, implying that characterizing the network helps to predict the network better. However, it is worthy to note that some goods categories such as iron steel and mining (other) have low percent variance explained. Only six goods movements, i.e., chemicals, fuel, meat and livestock, fish, crude oil, and fertilizer, are explained better by the network parameters, indicated by relatively high variance explained of more than 60%.

5. Conclusion
The present study aims at characterizing the network of goods movement in Indonesia and examining the effectiveness of network characterization for prediction purpose. The study has contributed empirically to provide insights on the network characterization of goods movement in Indonesia and has contributed theoretically to demonstrate the effectiveness of network characterization for prediction purpose.

Further, the study has highlighted that the network of goods movement in Indonesia is characterized by weak inter-provincial goods movement, scale-free network in which some provinces act as hubs and the probability of a province to connect with others following preferential attachment, disassortative which indicates that the provinces with high intensity of goods movement tend to establish relationships with other provinces with low intensity of goods movement, rich-club phenomenon where provinces with high strength will tend to be clustered with provinces with high strength, having a core-periphery structure with the provinces of Sumatera Barat and Jawa Barat acting as the cores of the network.

The parameters obtained from network characterization were used to predict the volume of goods movement. Contrasting with the prediction model based on gravity model parameters, the prediction model based on characterized parameters performs better and can explain about the average of 39% variance. The prediction model performs even better for chemicals, fuel, meat and livestock, fish, crude oil, and fertilizer, which can explain more than 60% variance.

It is also worth noting that the network characterization was conducted under normal conditions. As network can be disrupted such as due to the current COVID-19 pandemic, it opens potential research venues to characterize the network during disruption and therefore to investigate the resilience of the network.

6. References
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