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Modeling and Characterizing the Core-Periphery Structure of the World Airline Network

MSc Thesis in Physics

by

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Abstract

The stability and efficiency of the global network of commercial airline connections has become a vital part of our globalized society. Going beyond empirical analysis, we present here a model trying to understand the formation of the world airline network (WAN) from basic principles. In an iterative algorithm, our model employs two opposing forces: A passenger's desire to fly on non-stop flights whenever possible and an airline's strive to maximize profitability of each connection. As a function of a profitability threshold, we identify three distinct families of networks with a fully-connected, a core-periphery, and a tree-like structure, respectively, as outputs of this algorithm. Characterizing the regimes using several different metrics, we show that our model is able to recreate the unique core-periphery structure of the empirical WAN. Remarkably, in this regime of networks, the passenger load on each flight (airlines' profitability) is maximized while the average shortest path (passengers' convenience) stays stable. However, comparing results of a connectivity robustness analysis, we also find that the modeled networks are more robust than the real-world network, suggesting that further development of our model may help to improve the current state of the world airline network.

Declaration

I hereby declare that I have produced this Master Thesis without the prohibited assistance of third parties and without making use of aids other than those specified. All work presented has been conducted and interpreted by myself; notions and content taken over directly or indirectly from other sources have been identified and cited as such.

I confirm that this declaration is in accordance with the Declaration of Originality form required by ETH Zürich, which I have signed and submitted simultaneously with this thesis.

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Chapter 1

Introduction

1.1 Background and Motivation

In the last few decades, the methods used to study complex networks have successfully provided new tools and approaches to describe phenomena and complex interactions across many disciplines. Largely driven by the rapid advance of computational power, the abstract mathematical field of graph theory has quickly matured to be applicable in areas like statistical physics, computer science, logistics, biology, neuroscience, economics, and the social sciences, describing and modeling systems like the Internet, scientific collaboration, power grids (1), disease spreading (2), or opinion formation (7).

In particular, a network science approach has been applied to analyze the structure of the network of airline connections between airports globally. The world airline network (WAN) has become an important part of the infrastructure of our globalized society. Despite higher fuel prices and a wider consciousness for reducing carbon emissions, airplane travel is on the rise globally and can be predicted to grow in the future (4). Events like the shutdown of European airspace due to the eruption of the Icelandic volcano *Eyjafjallajökull* in 2010 demonstrate how essential safe and reliable airline traffic has become (3).

1.2 Literature Review

Airline networks have already been subject to a lot of network-related research. The WAN can be analyzed as a network (graph) in which airports (or cities) are represented by nodes and commercial scheduled flights as edges. Based on this network, which can represented by an adjacency matrix, one can use mathematical metrics and network-science techniques to investigate the underlying structure and resilience of the WAN. Using this approach, the empirical world-airline network has been found to be scale-free, i.e. the degree distribution follows a power law (14). Others have been concerned with centralities and community structures, showing that well-connected cities are not necessarily the most central from a network point of view (6). Due to the importance of the stability of global air traffic, a lot of studies have been concerned with assessing and improving the robustness and failure-resilience of the WAN (10, 12, 14).

One important empirical characterization has been that the world airline network exhibits a unique core-periphery structure, i.e. it consists of a small fraction of core airports that are nearly fully connected to each other while the larger part of the network forms the periphery, usually connected to the core via regional or national hubs (12). This property will be used in this work as a characterizing feature of the world airline network.

The major goal of this paper is to depart from a purely empirical analysis of the WAN and employ a modeling and simulation approach, which relatively few works have been concerned with thus far. One example is the model by Louf et al (9) proposing a cost-benefit driven optimization based on physical distances in transport networks. However, in airline traffic, physical distance is not necessarily the main factor driving costs since no roads or other distance-proportional infrastructure is needed. Hence our model expands this idea by including not only a notion of Euclidean distance, but also of (passenger) loads being carried on flights which are the main factor determining profitability of a link.

1.3 Airline Network Modeling

In order to possibly improve the efficiency and resilience of an airline network, it is of fundamental importance to understand in more detail how the current structure came about. In particular, the aforementioned core-periphery structure is a non-trivial peculiarity that we have set out to understand with an iterative algorithm modeling the WAN.

The current state of the network grew organically as a result of a complex interplay of (among other factors) economic considerations of airlines as well as political ties between countries. In theory, each airline aims to provide a network to best serve their customer's demands as well as maximize profitability. Most major airlines nowadays employ a "hub-and-spoke" philosophy in which passengers are routed through a central airport that serves as the airline's hub and base. In recent years, however, especially low-cost airlines (e.g. *Ryanair* in Europe) have rediscovered the "point-to-point" philosophy, providing non-stop flights whenever sufficient demand exists (14).

Our model takes the latter approach as the theoretical basis for creating a network-building algorithm. The algorithm contrasts two basic principles that we assume to be relevant when an airline connection between any two cities is formed:

1. Convenience of direct connections: For passengers, it would be most convenient to be able to fly non-stop between any two cities.
2. Profitability of flights: Commercial airlines will only offer a direct connection when it is profitable, which implies that a certain minimum number of passengers expresses demand to fly on that connection.

Through the interplay of these forces, we show that our model is able produce sets of networks which closely resemble some features of the WAN, in particular the existence of a core-periphery structure. We characterize the resulting networks using conventional metrics from network theory as well as non-traditional analyses such as the triangle-core decomposition proposed by Verma et al (12).

Although our model assumes that the network grows as a global entity (as opposed to each airline managing its own network), it does provide an interesting tool to produce a realistic result based on the simple counter-forces of convenience and profitability.

In doing so, it hints to an interesting conclusion regarding the two major theoretical approaches airlines employ (hub-and-spoke versus point-to-point). Even though our model is based on the latter approach, it does reproduce a real-world network (containing a strongly connected core of hubs) in which the former is the dominant philosophy.

Chapter 2

Model and Methods

2.1 Underlying Definitions and Assumptions

We assume the world airline network to be a network represented by an adjacency matrix $A_{ij}(N, V)$ with N nodes representing airports and V edges denoting whether or not a commercial flight exists between two airports. An edge is characterized by its physical length d_{ij} (distance between the airports, in km) and the passenger load l_{ij} (number of passengers traveling on that flight per an arbitrary time interval). Furthermore, we assume the network to be undirected, i.e. a connection is always operated in both directions equally, which is true for the overwhelming majority of real flights. Mathematically, this makes the adjacency, distance, and passenger load matrices symmetric. Self-edges are disregarded in all cases, such that $A_{ij} = 0$ for $i = j$. This holds implicitly throughout this work, even if not explicitly mentioned at each point.
We also take our modeled networks to consist of only one connected component, which is consistent with the empirical reference data also being a connected graph.
Additionally, we introduce a popularity p_i for each node, describing how many passengers are expected to be traveling to or from that airport.

As already mentioned in the introduction, we are using empirical data on commercial aircraft movements as a reference network. The data is taken from the open-source database *Openflights* (11) and is freely available. Our reference network, downloaded in May 2013, contains $N = 3237$ airports and $V = 18125$ direct connections.

2.2 Model Definition

As introduced in section 1.3, our model aims to reproduce the world airline network's structure by starting from simple principles, contrasting firstly passengers' desire to fly on non-stop connections and secondly airlines' profitability restrictions, requiring a certain number of passengers on each plane. We use this logic to justify the following initial setup and then define a step-wise algorithm that produces a structural model network of the WAN.

2.2.1 Initial Setup and Parameters

1. Start with a fully connected network with N nodes, i.e. $A_{ij} = 1 \ \ \forall i, j$.

2. Generate a random distribution of popularities p_i, which follows a certain probability distribution, (usually either uniform or power-law).

3. Define the passenger load l_{ij} of an edge to be the product of the popularities: $l_{ij} = p_i \cdot p_j$.

4. Generate a random distribution of distances d_{ij}, usually following the distance distribution of the empirical airline network by drawing a random sample for each d_{ij}.

5. Define a profitability threshold ϑ which is the minimum number of passengers required for an airline to maintain a direct connection.

2.2.2 Network Evolution Algorithm

When simulating a network starting with the above initial conditions and parameters, the following iterative algorithm is applied to evolve a network:

1. Create an ordered list of the passenger loads l_{ij} and choose the connection with the smallest load l_{ij}^{min}. If there are several pairs with an equally small load, choose one randomly.

2. If the load of the chosen connection falls below the profitability threshold ϑ, delete the corresponding edge, i.e. $l_{ij}^{min} < \vartheta \;\rightarrow\; A_{ij} = A_{ji} = 0$

3. Check whether by removing this edge the network is still connected.

4. Only if it has become disconnected, reverse the removal (restore $A_{ij} = A_{ji} = 1$), mark the edge as "essential" to the network such that it does not get chosen for removal again and continue with the next iteration.

5. Use Dijkstra's algorithm to find the new shortest path between i and j given that their direct connection has been deleted. When finding the shortest path, take into account the physical distances d_{ij} as edge weights.

6. "Reroute" the passenger load of the deleted connection to *each* edge that is part the new shortest path. For example, if the shortest path between i and j passes through k, set $l'_{ik} = l_{ik} + l_{ij}^{min}$ and $l'_{kj} = l_{kj} + l_{ij}^{min}$ (likewise in the other direction, retaining symmetry of l_{ij})

7. Mark l_{ij}^{min} as "removed" and repeat until no non-essential edge falls below the threshold ϑ.

In this paper, we often execute sweeps of this algorithm, with the profitability threshold ϑ as a parameter.

Using this simple yet non-trivial algorithm we model the two assumptions of convenience versus profitability. By starting with a fully connected network, a maximum though hypothetical degree of convenience is presumed: A passenger could travel non-stop from any city to any other city in the world. By removing connections below a set profitability threshold starting with the least profitable connection the second assumption of profitability is taken into account. Naturally, the few passengers traveling on an unprofitable flight are rerouted through the next-best connection, which potentially turns these alternative flights into (more) profitable connections. However, by imposing the condition of connectedness onto the network, we do assume some degree of "benevolence" of airlines over pure profitability optimization as no city or airport would be completely cut off from the network and the WAN would not be allowed to become fragmented.

2.3 Triangle-Core Decomposition

The generated model networks produced by the algorithm will be analyzed and compared using some well-known network theory metrics which are defined in detail in the supplementary information A.

However, one non-trivial method used to analyze in particular the core-periphery structure of airline networks is the triangle-core decomposition as proposed by Verma et al (12). Similar to the well-known k-core decomposition, the t-core decomposition removes nodes iteratively and assigns a "coreness" to them in the following steps:

1. Count the number of triangles each node is a part of. A node is part of a triangle if two of its neighbors are also connected to each other.
2. Remove all nodes that are part of $t = 0$ triangles. Recursively also remove all nodes which by this removal are part of $t = 0$ or less triangles.
3. Assign the t-coreness $t = 0$ to all removed nodes.
4. Repeat with $t = 1, 2, 3...$ until all nodes have been removed.

By simple combinatorics, the maximum possible t-coreness of a node in a network can be found to be:

$$T = \frac{(N-1)(N-2)}{2} \tag{2.1}$$

To make the coreness comparable across different system sizes, we will consistently use the relative t-coreness τ given by:

$$\tau = \frac{t}{T} \tag{2.2}$$

The reason we chose to employ the stricter triangle-based decomposition as opposed to the degree-based k-core decomposition to assess the core-periphery structure of a network lies in the fact that we are dealing with airline and passenger transport networks: In this context, being part of a triangle can be seen as particularly valuable for an airport because it allows passengers to reach a destination with only one layover in case the direct connection becomes temporarily or permanently unavailable. For instance, an airport that is part of the nearly fully-connected core of a network will be able to offer passengers many alternatives (as many as there are nodes in the core) to a faulty connection. Thus the t-coreness is especially suitable to assess which nodes belong to the core or the periphery.

2.4 Core-Periphery Metric

The relative t-coreness τ is a good way to measure whether a single node is part of the core of a network. However, in the results section of this paper we will compare whether entire networks exhibit a core-periphery character on an aggregate level. To do this, we define a core-periphery (CP) metric λ:

$$\lambda = (\tau_{max} - \tau_{min}) \frac{S_{\tau_{min}}}{S_{\tau_{max}}} \tag{2.3}$$

where τ_{max} and τ_{min} stand for the maximum and minimum relative t-coreness found for a given network respectively and $S_{\tau_{min}}$ and $S_{\tau_{max}}$ for the relative number of nodes that were assigned the respective coreness.

We define a network with a core-periphery structure to have both nodes with very low t-coreness (the periphery) and nodes with very high t-coreness (the core). Thus the difference of the maximum and minimum relative core-values is one factor in the CP metric. Additionally, λ is weighted with the ratio of the number of nodes belonging to the minimum and maximum t-core shells. This is done to account for the empirical fact that the core of the real airline network is very small compared to the periphery (12), so a network maximizing the ratio $\frac{S_{\tau_{min}}}{S_{\tau_{max}}}$ can be said to exhibit a particularly strong core-periphery character.

The rationale behind this definition is based on qualitative experience with the empirical network, which distinctly exhibits the conditions described above, maximizing λ when they are fulfilled.

2.5 Connectivity Robustness

As an additional method of comparing modeled networks to the real WAN, we use a connectivity robustness measure as defined in (12). For a given network, it assesses how robust the connectivity of the largest connected component is against the removal of nodes or edges. The following iterative steps are taken when removing nodes, with a), b), and c) denoting three separate versions of the removal procedure:

1. Create a list of nodes ordered by their degree.
2. Remove the node with the a) maximum degree, b) minimum degree or c) a random node.
3. Measure the size (relative to the system size N) of the largest connected component $S(q)$ as a function of the fraction of removed nodes q and repeat until all nodes have been removed.
4. Plot $S(q)$ versus q to obtain a characteristic robustness curve.

Similarly, the same procedure can be applied to edges by ordering them based on their passenger load and removing them in strategies analogous to a), b), and c).

Chapter 3

Results

3.1 Parameter Values

Unless stated otherwise, the results are based on the following initial parameter values:

1. $N = 1000$ nodes
2. Popularities p_i are distributed either

   (a) uniformly with values on the interval $[10, 30]$ *or*

   (b) following a power-law with $P(p_i) \sim p_i^{-2.5}$

   The initial probability distribution of popularities and the resulting distributions of the passenger loads $l_{ij} = p_i \cdot p_j$ are shown in Fig. 3.1. Note that only in case (a) there is a characteristic scale in l_{ij} with a well-defined minimum and maximum number of passengers l_{min} and l_{max}, respectively.

3. Distances d_{ij} are drawn randomly from the distribution of physical distances of the empirical network, which have been calculated from the real geographical positions of the airports. Hence the distribution of d_{ij} (Fig. 3.2) is of the same type as the empirical distribution, but the distance of each individual edge does not have exact correspondence with an edge in the empirical network.

The profitability threshold ϑ is varied as an independent variable and various properties of the network are investigated as a function of this parameter. Specifically, we let ϑ assume values from 0 to the sum of all initial passenger loads and perform sweeps of the evolution algorithm with these different values.

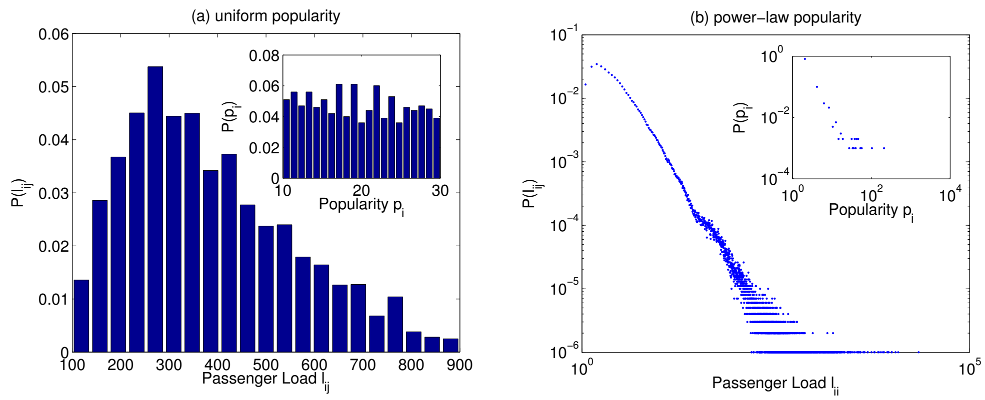

Figure 3.1: Initial distributions of parameters: a) Distribution of passenger loads l_{ij} on all connections in the initial network for the case of a uniform distribution of node popularities p_i (inset). b) Shows the same distribution assuming popularities which are initially power-law distributed

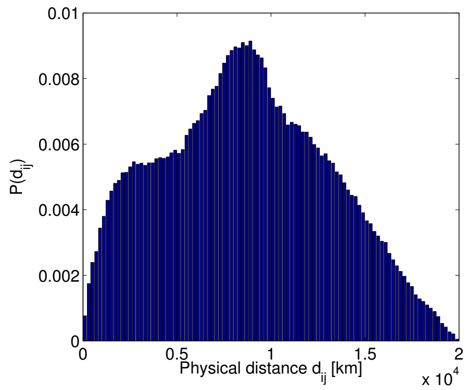

Figure 3.2: Distribution of physical distances d_{ij} between nodes in the initial state of the model network. The distances in the empirical network and the modeled network follow the same distribution

3.2 Established Network Metrics

Fig. 3.3 shows the dependence of some well-known network metrics as a function of the profitability threshold in the case of an initially uniform popularity distribution (case (a)). Note that all plots are on double-logarithmic scales.

The overall trend of all metrics is straightforward to explain: It makes intuitive sense that when removing connections and redistributing their passenger loads to other existing edges, the modularity, average load and average shortest path will increase while the average degree and the average cluster coefficient will decrease. However, it is worth noting that almost all curves exhibit a kink at $\vartheta = l_{max} = 900$. In the initial distribution of loads (Fig. 3.1a), this is the maximum load value of the initial distribution. Hence the kink in the metric occurs when all edges with the "original" passenger distribution have been removed, dividing the space of output networks of our algorithm into distinct regimes. Another regime or "family" of networks is apparent for all values of $\vartheta < l_{min} = 100$.

Thus three regimes can be characterized in the following way:

1. Regime A ($\vartheta < l_{min}$): In this case no edges have been removed since all passenger loads are above the threshold ϑ, hence the network is still **fully connected**.

2. Regime B ($l_{min} < \vartheta < l_{max}$): In this regime the network undergoes its most rapid change in terms of classical network metrics. Further analysis in the next section shows that this class of networks exhibits a **core-periphery structure** and thus best resembles the real-world airline network.

3. Regime C ($\vartheta > l_{max}$) finally shows comparatively small rates of change in the network metrics. For very large profitability threshold values, the core-periphery character breaks down and the number of essential edges rises rapidly: The network approaches a **tree-like structure**.

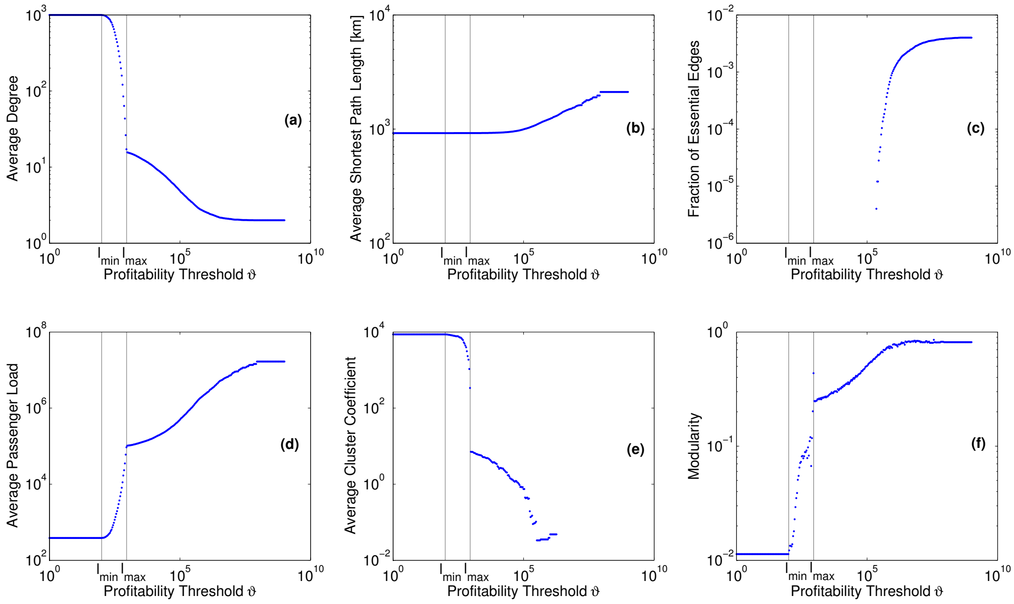

Figure 3.3: Various metrics and averages of the model networks plotted as a function of the profitability threshold ϑ with initial uniform popularity distribution. From left to right: a) Average degree of the network, b) average shortest path between all nodes, c) fraction of essential edges, d) average load of passengers on all direct connections, e) average cluster coefficient, f) modularity. The initial minimum and maximum values of the passenger load are marked by vertical lines, dividing ϑ into three regimes.

Additionally, the average shortest path length stays relatively stable over regimes A, B and parts of C, it only increases significantly when the fraction of essential edges also rises, thus when saturation in terms of edges that can be removed without disconnecting the network is reached. This is an interesting observation because it implies that passenger's convenience (short paths) remains high while airline's profitability (large average passenger load per connection) increases sharply.

The degree distribution is another important measure to characterize the topology of a network. Fig. 3.4 shows the of degree distributions of example networks from regimes B and C.

Note that when assuming an initial power-law distributed popularity (case (b) as described in section 3.1), no distinct regimes but rather smooth curves are obtained due to the lack of characteristic scales. Hence in the following sections, we will focus on the case of uniformly distributed popularities (case (a)) as these networks evolve into the non-trivial core-periphery structures that are most closely modeling the real-world network.

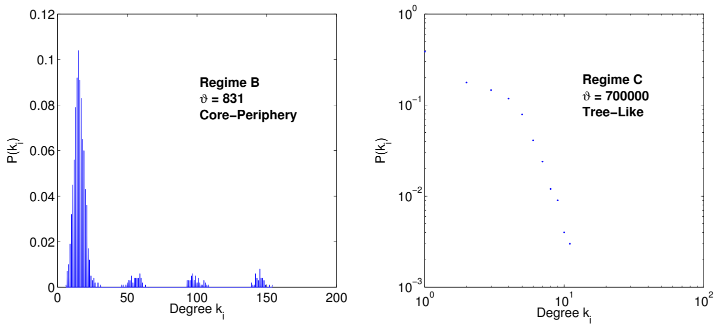

Figure 3.4: Degree Distributions of example networks from regimes B and C of the profitability threshold, representing networks with a core-periphery and tree-like structure, respectively.

3.3 Core-Periphery Structure

3.3.1 Core Size

For each network produced during a sweep, a t-core decomposition, as described in section 2.3, was performed to assess its core-periphery properties. We measured the core size S_{core}, i.e. the number of nodes relative to the system size N that are removed at the final iteration of the decomposition as well as the maximum relative t-coreness (coreness of the core) τ_{max}, both as a function of the profitability threshold ϑ. The results are shown in Fig. 3.5.

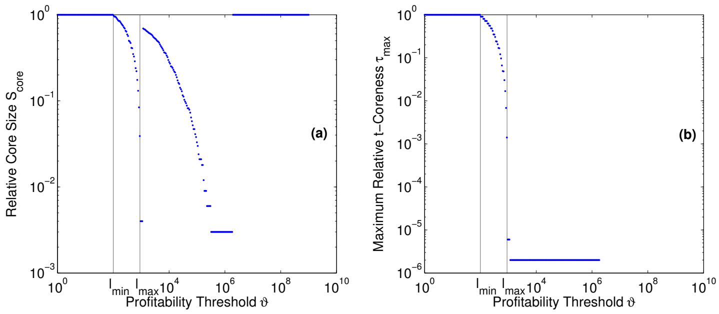

Figure 3.5: Characteristic metrics of the t-core decomposition: a) Relative size of the network core (fraction of nodes with largest coreness) and b) Maximum t-coreness (coreness of the core) as a function of the profitability threshold

In regime A (low values of ϑ), when the network is still fully connected, the core consists of the entire network at a very large coreness since there are many connections and thus many triangles. On the other end, in regime C (for very large ϑ), the tree-like network is sparsely connected such that it is essentially removed at the first t-iteration.
However, it is striking that between regimes B and C, the core size exhibits a discontinuity. The network undergoes a fundamental transition from a state with a small core and a relatively large coreness to a state in which the core is again comparable to the system size, but is of trivially small coreness. Since the empirical WAN is known to have a small

core size of approx. 2.3% (12) but high interconnectedness within the core (t-coreness), the most realistic networks are likely to be found in the regime B with $l_{min} < \vartheta < l_{max}$.

3.3.2 Coreness Distributions

To evaluate the core-periphery properties of the modeled networks, we generated histograms of the relative t-coreness of some exemplary networks in each regime as well as for the empirical network, showing the number of nodes removed at each t-iteration. All three are shown in Fig. 3.6. Qualitatively, the core-periphery structure is clearly visible in both regime B and the empirical network: The periphery consists of many nodes with small t-coreness, i.e. the distribution drops quickly with increasing coreness (note the semi-logarithmic scale). There are very few nodes of intermediate coreness, but the core is clearly visible as a small but distinct peak around the maximum coreness.
On the other hand, the t-coreness distributions of a network from the threshold regimes A and C exhibit a completely different behavior: In the case of a fully connected network (regime A), there is just a single peak at $\tau = 1$ and for the tree-like network (regime C), there is a single peak at $\tau = 0$, hence the entire network is removed at either the maximum or minimum iteration of the t-core decomposition. Due to their structural similarity, the distributions for regimes A and C are grouped in one plot.

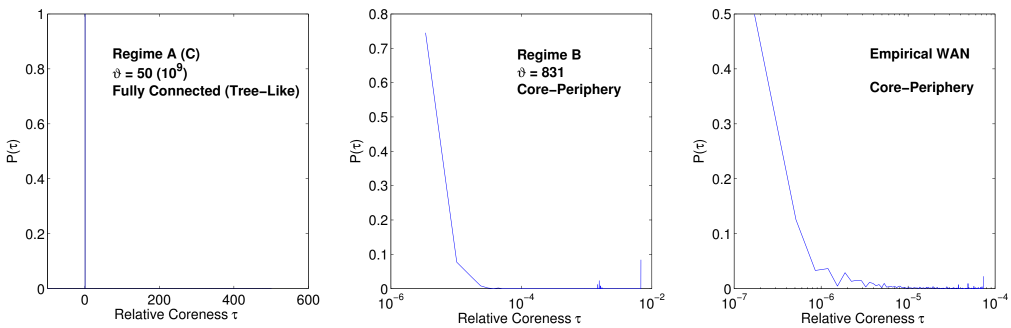

Figure 3.6: Distributions of the triangle coreness as the relative number of nodes: Examples from different profitability threshold regimes as well as the empirical network. Regime B and the real-world network exhibit a very similar core-periphery structure.

We can thus conclude that there indeed appears to be a sudden transition from a network with a characteristic core-periphery structure to a network eventually evolving into a tree-like topology when further increasing ϑ.

Fig. 3.7 further provides a visual illustration of the contrast between a core-periphery network of regime B and a tree-like network of regime C and the real-world network. It is clearly visible how the core-nodes (colored in red) are highly interconnected as they are grouped closely together by the fore-directed Fruchterman-Reingold algorithm (5). In the empirical network, it is also possible to see a fine separation of the core based on continents or world regions.

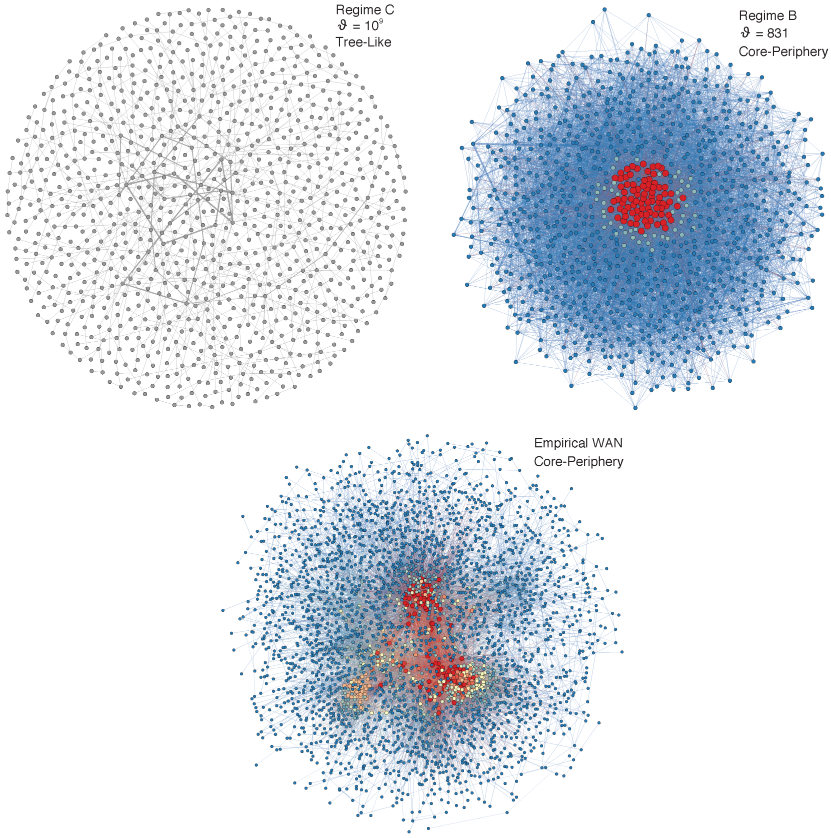

Figure 3.7: Visualization of network examples from different threshold regimes. The node layout was generated by applying the Fruchterman-Reingold algorithm (5). Color shades were chosen according to t-coreness with red indicating large coreness, blue indicating low coreness. Relative edge thickness is proportional to the passenger load.

3.3.3 Core-Periphery Metric

Although the aforementioned coreness histogram examples demonstrate qualitatively that the algorithm is able to reproduce the real-world network, we further developed the core-periphery metric λ to quantify the core-periphery character of the modeled networks with a single number. In equation 2.3, the CP-metric is defined in such a way that it is maximized for a network with a t-coreness distribution similar to the empirical core-periphery structure. Fig. 3.8 shows the CP-metric as a function of the removal threshold ϑ, illustrating that indeed for values of regime B, the modeled networks have a distinctive core-periphery character, especially for large values within regime B, close to l_{max}.

3.4 Connectivity Robustness

To further classify our model and compare its output to the empirical network, an analysis of the robustness against removal of nodes was performed, using the method defined in section 2.5. In Fig. 3.9, we compare the robustness curves from different threshold

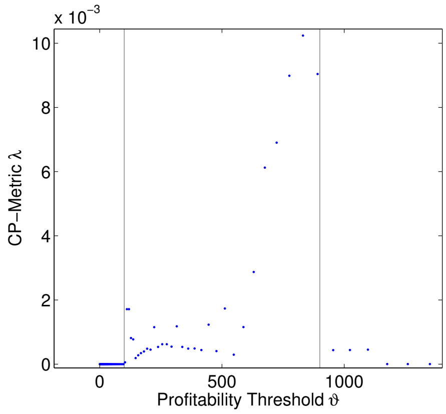

Figure 3.8: The core-periphery metric λ, designed to capture a core-periphery structure similar to the empirical network in a single metric, as a function of the profitability threshold. For the threshold regions identified as particularly similar to the WAN (vertical lines), λ is maximized.

regimes and the robustness curve of the empirical network. As presented in Verma et al (12), the empirical network is very sensitive to the removal of high-degree nodes as the size of the largest connected component drops very quickly. The network in regime A, previously identified as a good model of the real-world core-periphery structure, appears more robust, however: Even when removing high-degree nodes first, the network stays connected.

On the other hand, certain networks from regime C show a robustness pattern that is very similar to the empirical reality. We explain this discrepancy with the degree distribution of the two cases: In regime C, the degree is similar to a power-law distribution while in case (a) we observe several Gaussian-like peaks at a similar removal threshold (see Fig. 3.4). The empirical network is also known to have power-law distributed degrees. Since in scale-free (power-law degree) networks, the high-degree hubs carry the overwhelming majority of connections, the network will fail quickly when removing these hubs. Thus networks in regime C, although not producing a core-periphery structure, model the robustness of the empirical network much better. At the same time, however, we must also conclude that in regime B, previously identified to reproduce the core-periphery structure very well, we obtain a network that is much more stable to the closure of nodes or airports.

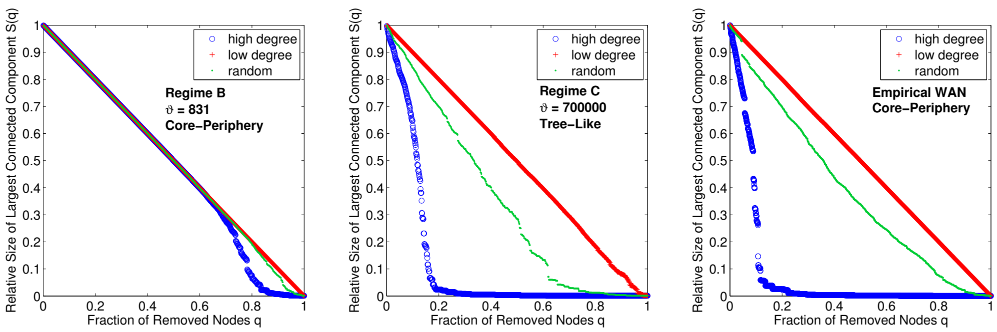

Figure 3.9: Connectivity robustness curves for networks from different network families, showing the fraction of nodes in the largest connected component of the network as a function of the fraction of nodes that have been iteratively removed. Three colors represent removal strategies: starting with the highest degree (blue), lowest degree (red) or in random order (green).

Chapter 4

Conclusion and Outlook

4.1 Discussion and Implications

In conclusion, we have presented an algorithmic model successfully replicating the core-periphery structure of the world airline network. Remarkably, this is possible using *only* the passengers' convenience of direct connections and airlines' maximization of profitability as two opposing micro-level forces. Indirectly, we are also taking into account the Euclidean distances between airports, following the same distribution as in the real world. On the macro level, simulating these forces on a network with no other fundamental assumptions, we obtain, for certain parameter regimes, a small core of densely interconnected airports and a periphery consisting of the remaining majority of cities. This structure had also been identified for the empirical network by Verma et al (12).

Furthermore, our model does not only provide a successful simlulation of the empirical reality. Apart from the fact that the range of parameter values we have identified to be producing a core-periphery structure best models the real network, other details make this regime particularly interesting. For instance, when a core-periphery structure is present, the average number of passengers on a flight (a proxy for the profitability of a connection) increases while the average shortest path between two airports (a proxy for passenger convenience) stays stable.

Merely when comparing the robustness of the network's connectivity (largest connected component) towards removal of nodes, our modeled core-periphery networks do not match the empirical reality. However, since our model produces networks that are more stable than the real network, it is legitimate to ask whether it could possibly be used to improve airline networks. Though very abstract and following a "proof-of-principle" paradigm in its current state, it might be possible to further develop our algorithm into a more practical simulation generating adivce for airlines seeking to improve the stability and efficiency of their networks.
This possibility hints to an interesting question regarding the two philosophies in providing passenger air service: hub-and-spoke vs point-to-point. Our model, removing connections iteratively, is based on the latter, but most major airlines employ the former paradigm. This fact provokes the question: Could our model's results hint towards a comeback of the point-to-point strategy in airline network design?

Needless to say, a mathematical model is always reductionist and highly simplified in its nature and cannot possibly encompass all relevant factors of reality, so one needs to be cautious to linearly apply its implications of the real world. For example, our model assumes that the world airline network is constructed globally, with all connections and passengers being treated equally. In reality, however, the worldwide network is just a sum of all airline's individual networks, who are not cooperating, but rather competing. On the other hand, the networks of large carrier alliances like *Star Alliance* could approximate the picture of a ”global network” in which our model could make suggestions for improvements assuming the partners in such an alliance are able and willing to cooperate. Apart from that, many low-cost carriers’ networks are already based purely on point-to-point profitability considerations.

4.2 Further Research

Apart from such long-term applications and implications, we can also identify more concrete further steps to test our model.

Specifically, our current results require the same empirical distribution of physical distances between airports in order to produce the core-periphery structure. It would thus be interesting to move towards the empirical network in a further step and take the *exact* positions of all airports as the nodes of a model network. The popularity of an airport can be made proportional to the population of the respective city, since it seems straightforward to justify that populous cities are more important destinations in global passenger traffic.
In other words: It would be interesting to see the product of our algorithm applied to conditions very close to the empirical reality as opposed making as few assumptions as possible when replicating the real network, which we focused on in this paper.

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Appendix A

Supplementary Information

Though they are commonly used in network theory, we provide the exact definitions of the network metrics used in section 3.2 for completeness and reproducibility.

Clustering Coefficient

We define the average clustering coefficient C of a network according to Watts and Strogatz (13):

$$C = \frac{1}{N} \sum_i \frac{2t_i}{k_i(k_i - 1)} \tag{A.1}$$

where t_i represents the number of triangles node i is a part of and k_i stands for the degree of i.

Modularity

We compute the modularity of a network as defined by Leicht and Newman (8). Let there be a quantitiy Q, defined by:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta_{c_i c_j} \tag{A.2}$$

where m represents the total number of edges, A_{ij} is the adjacency matrix, k_i is the degree of node i, δ is the Kronecker delta symbol and c_i is a label assigned to the community of which node i is a part of.
The quantity Q is maximized over all possible community divisions of the network. This maximum is then often referred to as simply "modularity" of the network.