Complex Systems Techniques applied to Transmission Expansion Planning.
Part II: An Agent-Based Model for Transmission Expansion Planning

María Pereda, Ilaria Bertazzi, Sara Lumbreras, Alice Patania, Jean-Gabriel Young, Daniel Citron, Masahiko Haraguchi

***Abstract*—Agent-based methods are useful for modeling complicated systems from the bottom-up. We propose an agent-based model to optimize the design of a power grid. The model is inspired by the behavior of the *Plasmodium* mould, whose feeding process is able to build efficient transportation networks as it feeds itself. Algorithms inspired by this mould have already been applied to road networks, but have never been explored in the problem of power network design given the added complexities of power flow. We propose a modification of the algorithm that includes the particulars of power systems and the related physics. The model is implemented in NetLogo and GAMS. This paper is the first step in introducing agent-based methods in power network planning.**

***Index Terms*—Transmission Expansion Planning, Agent-Based Modeling**

I. Introduction

AGENT-BASED modeling (ABM) is a consolidated methodology for creating computational models from a bottom-up perspective. The entities that compose the system are explicitly represented in the model as agents that interact with each other and the environment. The main advantage of ABM is that it facilitates the abstraction process since there is a direct correspondence between the entities and interactions in the model and the ones in the modeled system (Galán et al., 2009). These agents can represent individuals, groups of individuals (*e.g.* families or companies), or even abstract entities such as trading auctions in a market. The first agent-based models were developed in the 70's and 80's. Today, ABM is employed in many disciplines, including ecology social sciences, economics, and biology.

In ABM, the inference process is performed by computer simulation. Later, the researcher derives the general properties of the system by studying a significant subset of simulated cases (Galán et al., 2009).

As Bonabeau and others pointed out (Bonabeau, 2002), there are several system properties that make ABM particularly convenient as modeling tool: complex individual behavior and nonlinear interactions; heterogeneous populations; stochastic agent behavior or spatial and network distributions that are relevant for the overall behavior of the system.

II. The Slime mould in Human Transport Network Design

Biologically-inspired computation is a promising way to tackle organizational problems and develop good optimization methods. In particular, biological transportation networks, such as ant colony behavior or slime mould growth, can serve as an inspiration for human transportation network design,. We can consider these structures as information-transportation devices that perform adaptive changes in the structure of the network (and therefore to its transport performance) in response to stimuli that depend on their local environment. This ability to adapt is an emergent property that arises in anatomically simple organisms. In this sense, there is increasing evidence that the consideration of network function, rather than just network topology, may achieve global optimization through local adaptive responses for many network design problems.

In the case of biological systems, network development involves two phases: exploration and consolidation. The exploratory phase is characterized by the over-production of links and nodes. The consolidation phase, in turn, leads to the selection and positive reinforcement of some links, while destroying or recycling of the remainder. The sequence of overproduction, competition, and selection parallels the process of Darwinian evolution as well as other adaptive

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María Pereda is with Universidad de Burgos (e-mail: mpereda@ubu.es).
Ilaria Bertozzi with Università di Torino (e-mail ibertazz@unito.it)
Sara Lumbreras is with Universidad Pontificia Comillas (email: slumbreras@comillas.edu)
Jean-Gabriel Young is with Université Laval (email: jean-gabriel.young.1@ulaval.ca)
Alice Patania is with Politecnico di Torino and I.S.I. Foundation (email: alice.patania@polito.it)
Daniel Citron is with Cornell University (email: dtc65@cornell.edu).
Masahiko Haraguchi is with Columbia University (email.: mh2905@columbia.edu).

processes found in a wide variety of contexts. In the case of biological network evolution, the final network structure is likely to represent a context-specific balance between the need for efficient transport, low cost, and robustness.

The inspiration for this part of our power grid design project comes from the work of (Tero et al., 2010). In their article, which is based on biological experiments, the authors argue that the slime mould *Physarum Polycephalum* creates a network efficient enough to compete with the railway system around Tokyo. *Physarum Polycephalum* is a unicellular organism able to interact intelligently with its environment, exploring and adapting to it. In the plasmodium stage of its life, *Physarum Polycephalum* explores its environment and creates an intracellular network that connects to all the food sources it has managed to locate.

In this sense, we can consider the slime mould to be a computation device trying to create a viable network for communication and transportation under a set of constraints set by its environment. These constraints are either attractive (food, favorable temperature, etc) or repulsive (toxins, predators, illumination, etc.) fields in the environment surrounding the mould. *Plasmodium and Physarum* have been shown to be able to solve many computational problems, such as finding the shortest path (Nakagaki, 2001), constructing hierarchies of planar proximity graphs (A. Adamatzky, 2009),execution of basic logical computing schemes (A. Adamatzky, 2009; Tsuda, Aono, & Gunji, 2004). It is also capable of sketchinga mathematical model of an adaptive network that solves a convoluted maze (Tero et al., 2010). The key underlying mechanism is positive feedback: greater conductivity results in greater flux, and this in turn increases conductivity.

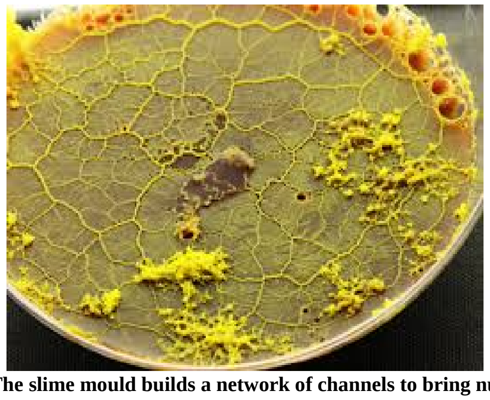

Figure 1. The slime mould builds a network of channels to bring nutrients efficiently to its core (Tero et al, 2007).

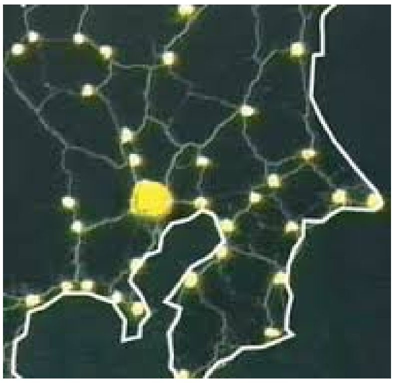

Figure 2. Transportation network built by the slime mould for Tokyo and its surroundings (Tero et al, 2007).

(Watkinson et al., 2006) provide an example of a similar work but with the fungus *Phanerochaete Velutina*. Many fungi form reticulated mycelia that constantly adapt to the environment. (Watkinson et al., 2006) show that fungal networks can display both high transport capacity and robustness to damage. These properties are enhanced as the network grows while the cost of building the network decreases due to selective reinforcement and recycling of transport pathways.

Some studies tried to replicate the behavior of this specific slime mould by extrapolating its behavioral rules and simulating them in an ABM model. For instance, (Takamatsu, Takaba, & Takizawa, 2009) developed a network growth model with simple local rules that replicates the behavior of the mould. In their work, their simulated result of growth area size, move distance, and reach distance disagree with the experimental result, whereas the dimensionless indexes such as circularity, fractal dimension, and flatness agree with the experimental results.

An extensive work over a biological approximation of man-made road networks, using real petri dish experiments of *Plasmodium* or *P. Polycephalum* placed in geographically-inspired environments, such as the United Kingdom (A. Adamatzky & Jones, 2009). All these works also allow for experimenting with disasters and disruption in the network structure.

These experiments with slime moulds and similar organisms, do have limitations when trying to use biologically-evolved networks to design human transportation networks. They require not only laboratory material and training, but also long hours of experimentation to find a stable path. Moreover, the constraints that can be represented in the mould environment are limited and very often fail to represent the details of human-created systems. Moreover, the process by which the specific mould develops its foraging network is not guaranteed to be optimal for any kind transportation network design, as different organisms have evolved to support different tasks and objectives.

To solve all of these problems, we propose to use a biologically-inspired network model incorporating positive and negative feedback on links and interaction with the environment (cost and distances) to develop a network of electrical transmission which is both efficient and robust.

III. ABM IN POWER SYSTEMS

ABMs have already been adapted for use by the power systems research community. In particular, the IEEE Power Engineering Society (PES) formed a working group to investigate the drivers and benefits of ABMs in 2007 (McArthur et al., 2007). The conclusions of the working group were that ABMs could, if used appropriately, be used as a modeling approach and for building flexible software systems in the power systems domain. The working group highlighted that ABM is a very natural way of modeling actors in some systems such as power markets. In a market, actors have attributes (such as prices) and possible actions (such as bidding or production in a generation market) which they take independently considering the characteristics of the environment. ABM can help understand the mechanics of such markets and the impact of changes in the actor attributes or behavior in the final outcome. The literature includes some examples of this type of study (Kiose & Voudouris, 2015; Shafie-Khah & Catalao, 2015). Among these recent applications, some of them study some specific aspects such as the dispatching of wind energy (Li & Shi, 2012), the modeling of demand elasticity through individual consumers (Karfopoulos et al., 2015; Thimmapuram & Jinho Kim, 2013), distributed generation (Divenyi & Dan, 2013), smart grids (Nguyen & Flueck, 2015; Niese et al., 2012; Prostejovsky, Merdan, Schitter, & Dimeas, 2013; Ross, Hopkinson, & Pachter, 2013) or micro grids (Chun-xia Dou & Bin Liu, 2013; Colson & Nehrir, 2011; Dimeas & Hatziargyriou, 2005).

In addition to market studies, ABMs have been applied to monitoring and diagnostics, given that power systems have a complex structure that needs to be managed using a very large set of data which is obtained in a distributed way (Davidson, McArthur, Mcdonald, Cumming, & Watt, 2006; Sharma, Srivastava, & Chakrabarti, 2015). For these reasons, ABMs have been used in the context of reliability analyses, post fault diagnosis (investigating the causes of a failure), or power system restoration (Davidson et al., 2006; Koesrindartoto, Sun, & Tesfatsion, 2005; Xu-Wen Yan, Li-Bao Shi, Liang-Zhong Yao, Yi-Xin Ni, & Bazargan, 2014). Other applications deal with control and automation (Buse, Sun, Wu, & Fitch, 2003; Chun-xia Dou & Bin Liu, 2013; Dimeas & Hatziargyriou, 2005; Divenyi & Dan, 2013; Nasri, Farhangi, Palizban, & Moallem, 2012; Prostejovsky et al., 2013; Ross et al., 2013; Yinliang Xu, Wenxin Liu, & Jun Gong, 2011). In addition, ABMs have been used as an optimization tool to calculate power flows (Nguyen & Flueck, 2015) or the economic dispatch (Kumar, Sharma, & Sadu, 2011).

IV. ABM AND POWER NETWORK DESIGN

Although there have been a range of applications of ABMs to power systems, these have been focused on market simulation, control and automation. Applying ABMs to power systems planning has been far more limited. In addition, almost all of them deal with generation expansion, the generation companies' decision to install new power plants. The use of ABMs for this problem is a result of the deregulation of the market, meaning that power expansion decisions are not made centrally by a system planner, but are decided by each company independently. In this context, it is intuitive to define generation companies as agents and use ABMs to study the impact of different expansion strategies. This has been done in works such as reference (Gnansounou, Dong, Pierre, & Quintero, 2004).

However, the authors could not find any literature that deals with the planning of the transmission network using ABMs. This is probably explained by the fact that, although the generation market was liberalized, the transmission grid is still planned in a central way in most countries (Lumbreras, 2014). We develop our model in the context of a liberalized generation market but centralized transmission planning (Hemmati, Hooshmand, & Khodabakhshian, 2013).

Therefore, the agent planning the grid is usually unique (the TSO or Transmission System Operator) and decides which new transmission assets to install based on considerations about the net social benefit derived for the system as a whole.

There are two references which deal with TEP (Transmission Expansion Planning) and ABMs, (Motamedi, Zareipour, Buygi, & Rosehart, 2010) and (Yen, Yan, Contreras, Ma, & Wu, 2000). Reference (Motamedi et al., 2010) performs transmission expansion planning using an ABM to consider the generation companies behavior, but does not use ABM to plan the transmission expansion itself. Reference (Yen et al., 2000) uses ABM to identify coalitions in the system that is groups of two or more agents that would benefit from acting together. In this paper, coalitions are more likely to build transmission lines if all coalition members receive increased benefits, which are assessed by means of the bilateral Shapley value.

Our work differs from these previous articles in two main ways. Firstly, they consider a context where transmission is deregulated, while we assume that transmission planning is performed in a centralized way in accordance with the structure of the system in most countries. Secondly, they define agents that coincide with real agents in the system – generator companies, retailers or merchant line operators –that maximize their individual profits. Our agents do not coincide with real companies and do not maximize their individual profits. Our agents are an interpretation of the cells of P. *Plasmodium*, which build a network to benefit the entire organism. It is important to note that our aim is not to simulate the behavior of the entities that use the power transmission network but to *create efficient power grid designs drawing inspiration from slime mould growth strategies.* In order to do this, we use agents that, like the cells in the *Plasmodium*, use local information to build the links in the network.

V. A MOULD-INSPIRED MODEL

The power grid presents additional features that make this problem more complicated than transportation network design:

- There are different types of nodes with different attributes; we have sources (generators) and sinks (loads), with different prices and capacities.

- While the most efficient way of taking food to the core of the slime mould is to follow the minimum-distance paths, the most efficient use of power transmission lines is more complicated. In order to know the best way of using line capacities, it is necessary to solve an optimization problem for system operation. This operation problem decides the optimal way of satisfying demand using the existent generators and considering their prices and capacities, as well as the capacities of the existent transmission lines and the physical laws that govern the power flows. We model and solve this problem using GAMS and then feed the results to the ABM. The complete formulation of the system operation model can be found in the appendix section.

In order to describe the agent-based model developed, we are going to follow the ODD documentation protocol (Grimm et al., 2006). The model is coded in Netlogo 5.2 and may be downloaded at the website www.openabm.org.

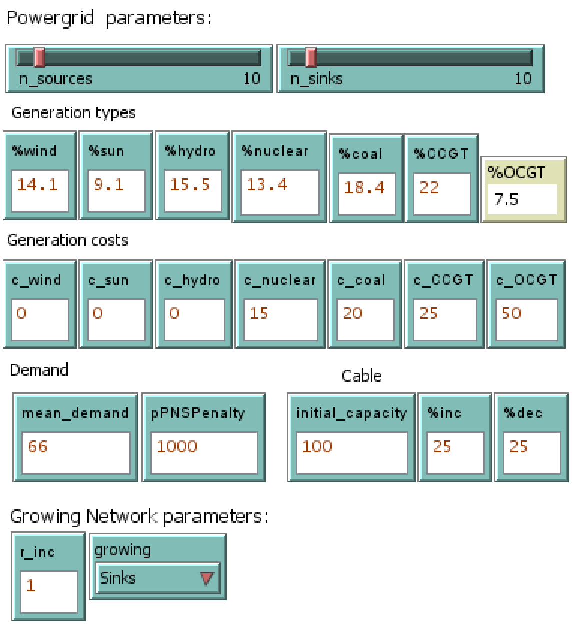

Figure 3. Input parameter area in "*Power Grid Mould*".

Power Grid Mould is a model that grows a biologically inspired power distribution network. The goal of the model is to create efficient power distribution networks with an optimization-based growing process that is biologically inspired and that takes into account investment and operation cost.

A. Overview: entities, state variables, and scales.

The model has three kinds of agents: sinks (demand), sources (generators), and links (transmission lines). Sources produce (generate) a certain amount of electrical power (variable "gen"), according to a maximum generation capacity. Sources have an attribute "type" that classifies them into different types. The type affects the maximum capacity and the cost of production, and models different production technologies. Sinks represent nodes where demand is located (urban or industrial centers). The number of sinks and sources is selected during initialization and remains constant during simulation. Source and sink agents are characterized by the state variables in Table 1 and Table 2. During each time step, sources and links can be linked together by means of a link agent. Links represent power cable and are characterized by the state variables shown in Table 3.

Attribute name	**Description**
s_type	Source type.
s_cost	Generation cost.
max_gen_capacity	Maximum generation capacity.
gen	Power generated at this node [MW]. It is the second-stage variable $g_{ti}^{\omega_t}$ in the appendix section.
r	Radius of influence to look for sources and sinks lo link to.

Table 1. State variables that refer to sources.

Attribute name	**Description**
s_type	Source type.
s_cost	Generation cost.
max_gen_capacity	Maximum generation capacity.
demand	Power consumed at this node [MW]. It is related to the parameter $D_{ti}^{\omega_t}$ at section in section in the appendix section.
r	Radius of influence to look for sources and sinks lo link to.
PNS	Power Not Served. It is related to the second-stage variable $pns_{ti}^{\omega_t}$ in the appendix section.

Table 2. State variables that refer to sinks.

VI. Attribute name	**VII. Description**
capacity	Maximum power that the cable can transmit.
cable_flow	Power that the cable is transmitting.
reactance	Reactance of the cable.
cable_type_capacity	Cable type, related to the indice variable c in the appendix section.

Table 3. Links state variables.

The environment is an unwrapped (normal, with boundaries) 2D square surface of dimensions 30 x 30 Netlogo patches. The model is also characterized by a set of global parameters and study parameters which define an experiment. These are summarized in Table 4, together with generation subtypes and generation costs.

Attribute name	Description
OptCost	Operation cost.
InvCost	Investment cost.
TotalCost	The total cost of the network results from adding the operation and the investment cost (TotalCost = OptCost + InvCost)
PNSCost	Power not served penalization.

Table 4. Global parameters. These are described in the next section in the appendix section.

Attribute name	Description
n_sources	Number of nodes of type source. The proportion of subtypes of nodes can be defined in each experiment, as Table 6 shows.
n_sinks	Number of nodes of type sink.
initial-r	Sources and sinks' initial radius of influence.
r_inc	Defines the new area of influence r' of a node, being multiplied by r in each time step.
initial_capacity	Initial capacity of the cable
%inc	Percentage of capacity increasing.
%dec	Percentage of capacity decreasing.
mean_demand	Mean of the exponential distribution that define sinks' demand.
pPNSPenalty	Penalty for Non-Supplied Energy.

Table 5. Study parameters.

A. Process overview and scheduling

Each time step, the following processes are executed in order:

- Update influence area of sources and sinks (*halo*), which defines the maximum area in which agents will contemplate the creation of links.
- Create new cables
- Calculate power flows. This step is carried out in GAMS.
- Calibrate cables – update cable capacity taking into account the information from power flows.
- Check convergence

These processes are described in section D. The order in which the agents perform the actions is random and the state variables are updated asynchronously.

B. Design concepts

The model grows an adaptive network design that pursues to minimize the total cost of the final design while respecting the laws that govern the power system.

C. Initialization

The initialization process is conducted by the user, choosing values for the relevant parameters. Nodes are placed randomly in the environment. Maximum capacity values for each source ("max_gen_capacity" parameter) are drawn from a uniform distribution on the interval [Capacity lower bound, Capacity upper bound], which present different interval bounds depending on the source's type, as shown in the tables. Sinks demand ("demand") is exponentially distributed, with a mean "mean_demand" parameter. More details on the specific values given to these can be seen in section VIII.

D. Submodels

1) Update influence area of sources and sinks.

The agents responsible for the search of new nodes to link to can be performed by sources only, sinks only, or both sinks and sources. This can be configured in the interface.

Each time step, the area of influence of the searcher node defined by the agent state variable *r* is multiplied by *r_inc* incrementing its magnitude. This means that, as the simulation runs, it considers linking nodes that are further and further apart. The relative speed of the growth of this area can be used to reflect different network architecture styles. If the area only grows slowly, shorter links are explored more, so that grids where there are predominantly local reinforcements are preferred. On the contrary, if the area grows quickly, long-range connections can be established, which fits the idea of *supergrid*-type architectures.

2) Create cables

Each "searcher agent" randomly selects a new node in its radius of influence, if any, and linkes to it. Each cable is created with capacity equal to *initial_capacity* parameter.

3) Flow

The optimal operation of the system for the current network is calculated by using a linear model coded in GAMS (see the appendix section). This model solves the operation of the system, which satisfies demand using cheap generators as much as possible, respecting the maximum capacity constraints for both generation plants and the cables. When a sink does not receive enough power to fulfill its demand, a new cost appears, which is called "Power Not Served" (PNS). This is penalized in the optimization problem.

4) Calibrate cables

The capacity of the cables is adapted at every time step, as the slime mold grows its connections to more profitable food sources.

Links which flow has reached the maximum value allowed by its capacity are updated to a higher capacity by a percentage defined by the parameter *%inc*. Analogously, those whose flow is inferior to the maximum flow permitted by the cable's capacity (and therefore are not used in full) have their capacity reduced by a percentage *%dec*. Cables which capacity is below a minimum capacity are deemed no longer economically viable and are deleted.

5) Convergence criterion

The simulation ends when a stationary state is reached. For checking the stationary state, we have used the coefficient of variance, as recommended by reference (Lorscheid, Heine, & Meyer, 2012). The coefficient of variance is a dimensionless measure of variance defined as the ratio between the standard deviation of the last *n* simulation results of the variable under study to the arithmetic mean of these measures. In our model, *n* can be selected in the interface to be the last five, twenty or hundred iterations, and the simulation stops when this coefficient is smaller than a fixed value.

VIII. Case Study

In order to get results that can be generalized, the ABM is applied to a set of problem instances generated at random following the statistical characteristics of the European power system (EWEA, 2015). Similarly, it assumes the costs and cable characteristics used in reference (Lumbreras, 2014).

Each simulation run specifies the number of generation and demand nodes, which are located randomly across a square with a side equivalent to 3000 km.

The model considers different types of generation: wind, sun, hydro, nuclear, coal, gas and fuel. Their relative characteristics can be seen in the table below:

Technology	Relative abundance (%)	Capacity lower bound [MW]	Capacity upper bound [MW]	Marginal cost [€/MWh]
Wind	14.10%	10	500	0
Sun	9.10%	10	500	0
Hydro	15.50%	10	500	0
Nuclear	13.40%	1000	1500	15
Coal	18.40%	500	100	20
CCGT	22%	100	500	25
OCGT	7.5%	100	500	50

Table 6. Characteristics of the generators.

Demand is exponentially distributed with an average value of 66 MW for each node. The penalty for Non-Supplied Energy (Power Not Supplied, PNS), that is, for not being able to satisfy demand, is 1000 EUR /MWh.

The agents can install transmission lines either in full (100% of their capacity), a fraction of their capacity (less than 100% of the capacity) or assuming several transmission lines can be installed in parallel (more than 100% of the capacity). The cable characteristics considered can be seen in the table below:

	Cable characteristics
Rated power [MW]	1213
Cost [M€/km]	0.525
Reactance [ohm pu/km]	0.008

Table 7. Characteristics of the transmission lines.

IX. Results

The parameter space of the model is potentially very wide, so in order to depict an initial sketch of how the results landscape may look like we decided to restrict our preliminary simulations to a narrow parameter subset. The number of both sinks and sources was fixed at 10, and we established an initial value for the capacity of 10% of the notional capacity of the transmission line.

The parameters that vary in this initial exploration are:

- What type of agent is allowed to create links from itself to its surroundings. This is equivalent to identifying the organism and the food in the biological metaphor. For example, if we identify sinks as the ones in charge of creating links, then the sinks represent the organism and the sources they connect to become the food sources. The reverse is also true when sources guide the network structure development. We also include the possibility that both types of agents are creating links.
- How fast each agent's area of influence (the space each organism "sees") increases. If it increases slowly, the network may take a long time to reach a state where long-distance cables are created, therefore implementing a more locally-based network. On the other hand, if the area increases quickly, it rapidly includes all the possible space, possibly considering supergrid-type networks that display many long-range connections but skipping useful local configurations.
- How cables adapt their relative capacity to their use in the network. As explained above, if a cable is not used at full capacity it slowly decreases its capacity to the point where it is eliminated from the network. If a cable is used at its full capacity, its capacity is adaptatively increased. The rates of these adjustments are two of the parameters of our model. We fix the level at which cables with very low capacity are deleted at 5% in this preliminary exploration.

How these parameters vary in our preliminar exploration experiment is summarized in Table 8:

Parameter	NetLogo Model Name	Value range
Who is creating links	growing	Sink / Sources / Both
Growth of the space of influence per tick	r_inc (in patch-distance 1 = 10km)	0.05 / 0.1 / 1.0
Percentage Adaptation of increasing cables	%inc	5 / 10 / 25
Percentage Adaptation of decreasing cables	%dec	5 / 10 / 25

Table 8. Parameter ranges.

With this narrow parameter range, we identified 81 (3^4) parameter combinations. We run the simulation 30 times for each parameter combination in order to get statistically sound results.

Each simulation run returns the investment cost, operation cost, and total cost of building the network. The simulation also returned cable capacities.

Our results reveal no clear pattern. Further exploration will depict a better view of the results landscape in terms of cost fitness and network structure for specific parameters combinations that could result in improved network configurations. However, some preliminary discussion is possible at this early stage of experimentation.

Figure 5 to **Error! Reference source not found.** through 10 depict different outcomes vs. average cost over 30 replications of the same parameter combination. We consider these results to be descriptive only and intend to only use them to guide our next research steps.

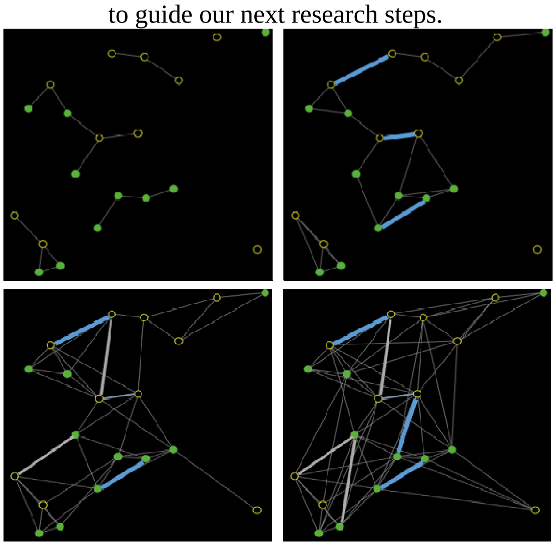

Figure 4. Example of evolution of a network in the developed model.

1) *Total Cost*

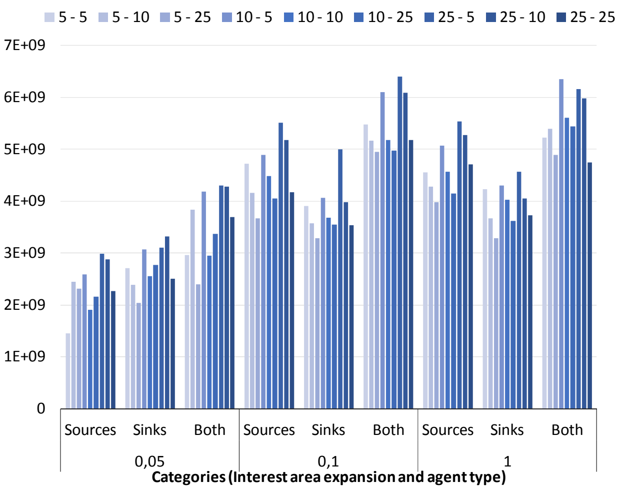

Figure 5. Distribution of total cost [EUR] in the preliminary experiments.

Total cost is the variable that gives the most information about a layout. It includes a measure of operation cost that decreases proportionally with PNS and generation cost, as well as a structural measure of transmission infrastructure investment cost. The latter is a function of the number of cables in the system, their type (not included in this preliminar exploration, but relevant for further ones) and length. Because the network is geographically embedded, the cable length distribution is an indicator of how local or global the network is.The highest peaks in total cost appear in the simulations where influence areas are grown most slowly (0,0.5), regardless of who is creating the links. A tendencey for higher cost, even though not equally distributed, is recognizable in the outcomes of simulations where only sources create links. The smallest total costs appear in the experiments where sinks are in charge of the network creation. This could possibly reinforce our biological metaphor for demand agents looking for energy/food-like resources in their sourrounding environment.

2) *Operation cost*

A major part of the difference in total costs terms appears to be related to operation cost. The plot is organized in the same way as the previous one. In order to understand where this difference comes from, we need to look at PNS, exploration which will be carried out in the next step of the research. This difference is particularly evident in terms of orders of magnitude.Figure 6 shows the operation cost distribution, with data points grouped according to which agents are responsible for creating links and the growth rate of influence. The operation costs vary over orders of magnitude as the growth rate of influence increases. Slow-growing networks (when r_inc is small) are more locally grouded, therefore they have a higher tendency for PNS at least at the first stages of the simulation. In addition, local networks can lead the flow optimization to solutions where the cheapest sources of energy available cannot be chosen, but nodes have to rely on the closest one in order to serve the demand. In order to understand where this difference comes from, we need to look at PNS, which will come in the next step of the research.

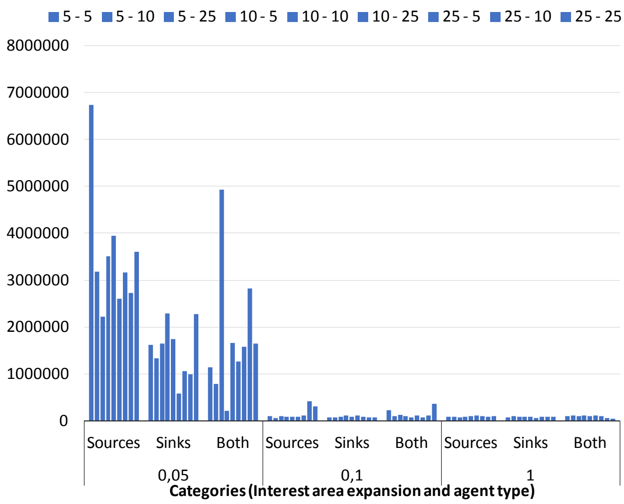

Figure 6. Distribution of operation cost [MEUR]in the preliminary experiments.

3) *Investment Cost*

In terms of investment cost (which appears here as a single figure, not discounted by the amortizing factor used in the total cost computation), it seems possible that this variable takes higher values for more global networks, where the radius of influence of each agent is grows relatively quickly. The network structure created is likely to have longer cables, therefore being more expensive in terms of infrastructure investment. The same consideration can be made when looking at the values of investment cost for the case where both types of agents are resposible for growing the network. In this case, a higher number of cables is possible, therefore increasing the cost of the infrastructure, at least during the early stages of a simulation run. Will will further investigate this pattern in the next steps of the research process, looking carefully at the network structure and cable length as the network configurations stabilize.

Figure 7. Distribution of investment cost [EUR] in the preliminary experiments.

4) *Energy generation at sources*

The first clear outcome in terms of energy production indicators is that the minimum generation of the sources of each simulation is alway zero, meaning that there is always at least one generation source which is not producing at all. This is due to the algorithm's preference for using the energy coming from the cheapest sources.

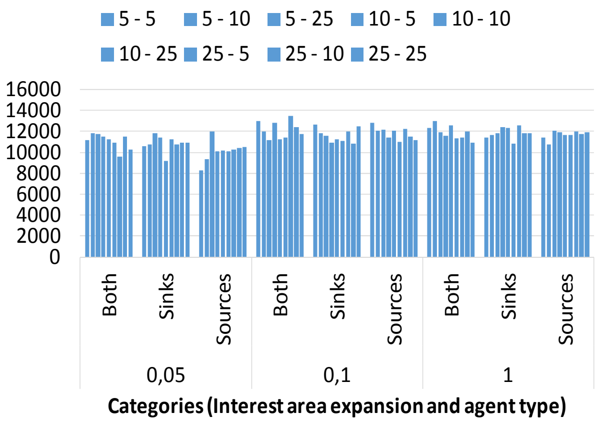

Figure 8. Distribution of source maximum generation [MW] in the preliminary experiments. depicts the averages over 30 observations of each parameter combination. [MW] No clear pattern appears.

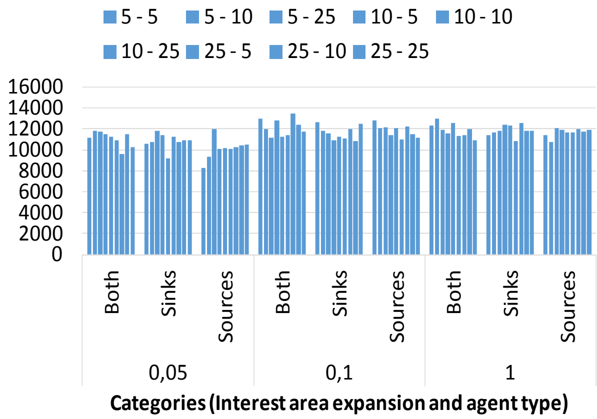

Figure 8. Distribution of source maximum generation [MW] in the preliminary experiments.

5) *Cable Capacity*

Cable capacity distributions can give insights into how the adaptation process of the network over its usage works. (Again, we will investigate this further in the next steps of research.) Given the present results, we can hypothezise that, intuitively, the average cable capacity increases as the adaptation process becomes more sensitive to capacity increases (the percentage increase of capacity when it is used in full) and decreases when the opposite process gains weights (the percentage decrease of capacity when it is not used in full.).

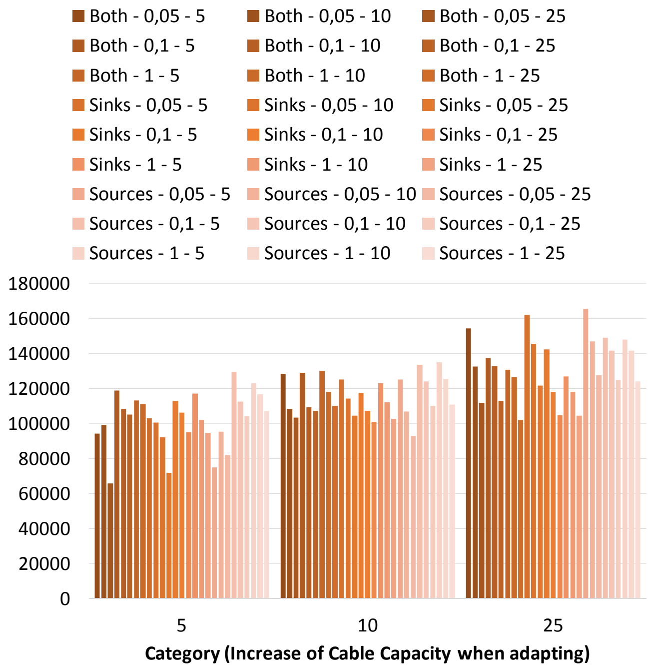

Figure 9. Distribution of average cable capacity in the preliminary experiments.

In terms of maximum value, cable capacity does not seem to display any obvious differences as the adaptation parameters change.

X. Conclusions and Further work

We have developed an ABM to optimize power grid performance with respect to costs. The model is inspired in the behavior of the *Plasmodium* mould, which has already been applied to the design of transportation networks.

Nodes identify other nodes in their proximity and can link to them by a transmission line. The definition of the neighborhood of a node grows with time, so that as a simulation run progresses, transmission lines can be built between nodes that are further apart. This reflects the fact that the power transmission network is spatially embedded and lines are more expensive the longer the distance they stretch across.

Once new links have been placed, the operation of the system is calculated by an optimization model that takes into account generation and transmission capacities as well as the Kirchhoff's Laws that determine the physics of power flows. Lines that are used in full increase their capacities, while the ones that are not fully exploited decrease it. The model is implemented in NetLogo and uses GAMS to perform the optimal operation of the system.

We studied the effect of the different parameters of the model, as well as the impact of letting sinks, sources or both types of nodes be responsible for the expansion. It seems that the parameters with the largest effect the most in terms of costs are the speed of growth of the area of influence of the agents that grow the network. This speed of growth is related to the tendency to have more local reinforcements versus more long-range corridors (as in the so-called supergrid). The investment cost in this case study grows with the number of possible links available, that is, investment cost tends to be higher when both sources and sinks can create links and when the area of influence grows more quickly.

The next steps of this research should focus on:

- Comparing the performance of the ABM to classical methods (Mixed-Integer Programming, MIP). This could be made by means of a modified GAMS model that could return the optimal solution for the network.
- Modifying the ABM to consider discrete investment. This can be done in a relatively easy way, defining several discrete cable capacities and modifying the capacity increase/decrease rule to choose from among these allowed capacities during each time step. This discrete version of the ABM should also be compared to MIP.
- In addition, the problem could be extended to consider several operation scenarios. Similar versions of the rules can be used. The performance of this stochastic version should be studied.
- The increase rule we have used focuses on the use of a line. Alternatively, other rules can be used. An alternative that seems particularly interesting is the marginal value of capacity, which can be obtained as a result of the optimization model used for determining system operation.
- In order to enlighten the relationships between model's parameters and the response behaviour under study, a complete space of parameters exploration and simulation result analysis must be conducted. To do so, we plan using Machine Learning tecniques to find patterns that will allow us to infer explanatory generalizations. ABM models have proven successful in other design problems and could be in this field too. We have carried out the first steps of a research line that could bring this tool to Transmission Expansion Planning.

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