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Principles of Neuroempiricism and generalization of network topology for health service delivery

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Abstract: Neuroempiricism describes a strategy to store and process data analogous to the human brain and to derive an adaptive representation by modelling the biological processes. Technical systems often copy biological evolutionary “developments” from nature. The neuroempirical principle is an approach to realise features of biological information processing for technical approaches or solutions.

It is a challenge to model spatial problems in healthcare like the dissemination of a viral infection. The characteristics of the infection are changing in time and often further complicated by unpredictable events such as mutation of the virus. These factors have to be accounted for in the computer based framework of the model. Artificial Neural Networks (ANN) can be used as a mathematical and informatics module embedded in a Decision Support System for risk assessment and the distribution of related medical services. This article describes the application of Neuroempiricism for modelling complex dynamic systems in healthcare informatics which results in a new extended network typology derived from a biological network. The new model extends directed weighted graphs to a topological non-equivalent network model that is able to represent biological axo-axonal junctions. The new network topology creates a data structure for computational decision support concepts. The Biological Neural Network (BNN) provides an extension of the ANN so that both fuzzy and crisp data can be processed in a unified network typology.

Keywords: Neuroempiricism; Decision Support systems; Neural Networks

1 Introduction

The results of this paper contributes to the development of an Early Warning And Response System (EWARS) for infectious diseases as an Open-source software framework. EWARS is a Spatial Decision Support System (SDSS) that supports decision maker to deploy medical resources in space in time according to a spatial distribution of epidemiological risk. A SDSS will not make decisions on its own, instead it will enable the decision maker to consider more parameters in a complex medical environment to optimize the decision making process. Because "complexity" is used in a more generalized sense and it is at the same time a notion to express computational effort in Computer Science, we consider the notion in the context of decision support first. Then we introduce it to the application area of the SDSS in rural areas because health service delivery in these areas especially in developing countries suffer from the lack of medical resources. The objective of a spatial decision support provided by EWARS is to optimize the deployment of the existing limited resources in rural areas to improve health service delivery according to risk.

This paper will bridge the gap between the main objective of EWARS development on the one side and the underlying generalized network topology as a data structures in the Open-source framework on the other side.

Complexity and Decision Support

Complexity theory in the context of Computer Sciences (CS) provides measures for estimating the calculation effort. The calculation effort of an algorithm can be described as mathematical mapping from the length of an input sequence to the average effort for calculating the defined result. The mathematical expression provides the calculation effort depending e.g. linearly, polynomially, exponentially, - depending on the length of an input sequence. Another aspect of complexity focuses on the minimal length of an algorithm to generate an output sequence (Kolmogorov-Chaitin-Complexity $C(s)$). Let A be an algorithm represented by a sequence of bits. Kolmogorov-Chaitin-Complexity $C(s)$ of a finite binary sequence s is defined to be the minimal length of the sequence A to generate the object s by an algorithm A, that outputs s without any inputs. We keep the concept of measuring calculation effort and leave the notion of complexity in the context of computer science (CS-Complexity) for a more generalised view on complexity.

An interdisciplinary field of research for the examination and representation of complex dynamic systems examines complexity in the so-called general theory of complexity (Gell-Mann, M. [10] 1992 and [11] 1995/96). In this generalised approach to complexity incorporates aspects derived from economics, biological processes in ecosystems, evolution and behavioural research, medical processes in living organisms, aspects of cognitive sciences and physics with chaos theory. Health related systems are important examples of complex dynamic systems as exemplified below:

- Health of a human being is dependent on environmental conditions and appearance of diseases
- Life-cycle of pathogenic bacteria (interference with normal human metabolism by introducing disease),
- Life-cycle of a mosquito in combination with a pathogenic parasite to cause disease (e.g. Anopheles and Malaria) and
- Economical aspects of spatial distribution and deployment of medical goods and services in a healthcare system

Focussing on health service delivery all these layers of complexity are operating on different scales on one side and on the other side they have in common that they depend on a huge number of parameters. These layers are linked in a complex network and their characteristics are changing over space and time. For decision makers in the health care system like doctors, nurses and administration it is a big challenge to derive decision in a complex environment. Creating computer based models of a complex health environment with the means of medical informatics have the objective to guide decision makers by the development of a Decision Support System (DSS). We are starting with the assumption that no perfect computer science models exist, that describe a complex dynamic systems appropriately and so all models have to be refined in an iterative modelling cycle.

In this generalised meaning of complexity a DSS has to be adaptive because of the dynamics of complex medical environments. Measuring complexity for a decision support system means measuring quality of the prioritize options for decision making suggested by the DSS for the decision maker. Mathematically a DSS maps medical, environmental, economical and biological parameters in the input domain to decision options in the output domain. For an implemented representation of this mapping on computer systems the DSS has to be able to incorporate the iterative refinement of the decision support. Even if an algorithm might provide useful functional mapping between input parameters and the decision options with prioritization in the beginning, but after a while it is no longer in tune with a changing medical and human environment. This fact underlines the necessity for ongoing improvement of the DSS as described by Turban and Aronson [25] in 2000. To meet this requirement, the DSS will have to have a feature of artificial learning by using empirical data from the considered medical environment.

Decision makers have to decide anyway with or without DSS and with a DSS a decision maker could accept the prioritization of options provided by the DSS or decline the suggestions of DSS. The outcome of the final decision made by the decision maker is again the input for the DSS.

Health service delivery and Decision Support

Let us consider health service delivery to rural areas to demonstrate how the objective of an improvement of health service is embedded in a broader non-medical environment of rural communities. The healthcare delivery system of rural communities depends on this environment and infrastructure. The optimisation of health service delivery can be achieved by applying logistic support principles as described by Ackermann [1] in 2007. The complexity and ultimate capability of decision support systems will increase by considering these aspects in addition to the core of medical diagnosis and treatment. For spatial decision support the logistics part have to be considered at the response part of EWARS for an optimum distribution of medical resources according to risk.

Throughout the world, health service delivery to rural communities is neither as well described nor as developed as urban health delivery (Wonca [27], 2002). This implies that decision support has to deal with incomplete data. In addition to the constraints mentioned above, sustainable changes in the health service delivery cannot be considered isolated from technological, economical and social factors. For example, Jacobs & Herselman [30] have shown in 2006 that the development of the local economy in rural South Africa, and Africa in general, is severely compromised by the lack of infrastructure, services and know-how. Improving the economical situation of rural communities enables them to grow or buy more nutritious food which can be accompanied by enhanced education that helps to teach what “nutritious food” means. If the basic needs for food, clothing, shelter and clean water cannot be satisfied by an economically sustainable environment, health education and education in general is of low priority (Herselman [8], 2007). In such a difficult environment, technological devices and infrastructure provided is often sold for generating money or resources to satisfy short-term basic needs instead of having a long-term benefit by applying the technology for education, business, language and health. Cullen [5] (2002), Rao [16] (2003) and Herselman & Jacobs [13] (2005) determined these main factors that prevent rural businesses from obtaining benefits of ICT (Information and Communication Technology). These barriers to technology use range from a lack of physical access and language problems to affective, emotional and cultural obstacles.

Improvements in health service delivery have to be considered in a complex environment of individual technological, economical and social requirements and constraints in which rural communities are developing. This complex heterogeneous environment of rural communities is regarded as a learning system which learns by being exposed to technology, education and other changes of medical infrastructure. Thus learning does not take place only because of positive changes in the system.

A medical doctor has his expertise in medical diagnosis and treatment. In most cases a logistically optimised treatment incorporating a broader perspective is not the focus of a clinician. By implementation of an adaptive DSS, logistic support principles can be applied to and assist in reducing costs for the delivery of medical goods and services ([25] Turban, E., & Aronson 2000). To achieve this goal medical doctors, computer scientists, logistic support experts, mathematicians and ICT experts have to collaborate to realise a holistic problem solving strategy for health service delivery in rural communities.

Network Topology and Decision Support

In the context of the generalised notion of complexity and the assumption that no perfect model of a SDSS for early warning and response support will exist, we focus on the fact that a decision maker has to make decisions in early warning cases anyway and she/he has to deploy the existing resources. The decision maker must accept the fact that she/he does not have all the information about the medical, social, technological, educational and economical issues that are interfering with the decision making process. When a decision maker has to make a decision his decision will have consequences for the decision maker in terms of evaluating the first decision in relation to the outcome of his decision. In this sense decision making in general is an iterative cycle of failure and improvement of a decision making process. Supporting the decision making by an EWARS the basic underlying data structures is a network topology that should have the following properties.

- EWARS should be able to integrate expert knowledge for optimisation of decision in a discipline where the decision maker is not trained (e.g. support a clinician with logistics support strategies for an optimised deployment of medical resources). This means that an expert rule can be plugged in the underlying network topology and be able to be weighted due to changes in relevance of the rule in the optimisation process of decision making.

- EWARS should have an underlying data structure that is capable to represent iterative optimisation of decision making because the complexity (in the generalised sense) needs an iterative process of optimisation integrated in the system itself, this means that the output of one module modifies the weights of the network of on other module of the SDSS and vice versa.
- EWARS need a basic data structure for the network that is able to interface with a rule based system of expert knowledge that has the same underlying topological structure as a data type,
- EWARS need a spatial representation of the underlying data structure, so that every node in the network needs a spatial location.

In this paper it will be shown how a generalised topological network structure as a data type that extends the definition of a weighted directed graph in Computer Science provides an adaptive module for the decision support system for the optimised delivery of health services. The generalised topology defines the concept of dealing with empirical data and represents these data adaptively by using Artificial Neural Networks (ANN).

An ANN is a weighted directed graph with a learning algorithms that modifies the topology or the weights in the directed graph (Rojas [17]). A Biological Neural Net is a network of connected cells called neurons (human brain – average: 10000 connections per neuron). The neurons are able to send electro-chemical impulses from one neuron to another via the connection called synapse. Because the objective of this paper is to derive a generalised network topology for spatial decision support we do not discuss the existing learning algorithms of ANNs.

According to Niehaus [18] Neuroempiricism is a problem solving strategy to discover similarities in biological information processing and in information processing of a DSS. The objective of Neuroempiricism is to develop computational models that use aspects of information processing existing in Biological Neural Networks (BNN). Computational models which have the the ability to learn can be used to transform an existing static model of health service delivery with data resources to an adaptive e-health decision support system. Niehaus [18] described the framework of complex dynamic systems in 2007. In this article the ANN topology is extended according to features found in the BNN. These features of the BNN are new for application in DSS or ANN models. The complexity of a health environment and heterogeneous information processing of empirical data demands a unified network topology that enables simplified communication between the modules of a DSS.

2 Methodology

Neuroempiricism is an approach of transferring biological aspects of information processing to technical systems. In contrast to the original objective of Artificial Intelligence (AI) to generate artificial intelligence on computer systems the approach of neuroempiricism focuses on the realisation of adaptive modules in technical systems for processing empirical data. The scientific objective is pragmatic in that any knowledge transfer from a biological to a technical system should provide improvements of the technical system. Similarities in processing empirical data (e.g. geo spatial data of medical resources) and visual information processing in the brain (edge detection, motion analysis) and similarities of expected results in technical and neural processing of information processing determine the improvement of a technical system by transferring aspects of neural information processing to technical systems. In this article the methodology is applied to different types of data resources that will result in transferring aspects of neural topological structures to technical modules for processing similar empirical data in comparison to the brain.

Neuroempiricism focuses on adaptiveness of decision support systems. Adaptiveness is realised by the application of Artificial Neural Networks (ANN) and Fuzzy Logic in technical systems. Neuro-Fuzzy-Systems are already applied in technical systems by combining ANN and Fuzzy Logic in one single system ([32] Turban & Aronson). The methodology is used to transfer aspects of neural topological structures which can be found in the human brain to a technical topology of information processing and thereby simplifying the technical topology that is able to cover Fuzzy Logic and ANN and the information interchange.

The following figure indicates a default process of modelling and application of an ANN in a developed software system.

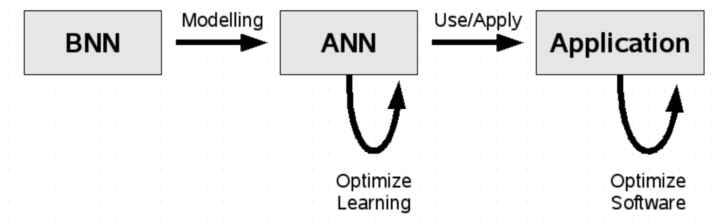

Figure 1: Modelling of BNN features in an ANN application

An ANN is created by modelling certain features of a Biological Neural Network (BNN). After the creation of the ANN model the ANN runs through cycles of software optimization to improve the properties of the ANN. Developed ANN models with determined properties of convergence will be used or integrated in software applications. The modelled features of the BNN are of minor interest. The developmental process of ANNs is driven by a mathematical analysis of convergence and by the capabilities of the ANN to solve classified problems in a software design process of applications. From the developers perspective the ANN is just an option in a wide range of tools from Artificial Intelligence, Knowledge Acquisition and Validation, Data Mining, Knowledge Representation and Inference Techniques as described by Turban and Aronson [25].

Neuroempiricism is a problem solving strategy that focuses on similarities of information processing directly between the final software application and the BNN. The similarities could determine the selection of ANN models or the modelling of BNN features in the developed application directly. The following figure shows the main cycles of development for the analysis of BNN features and the requirements of the developed application (in this case a DSS). The selection of appropriate ANN models is an implication of the analysis of similarities only.

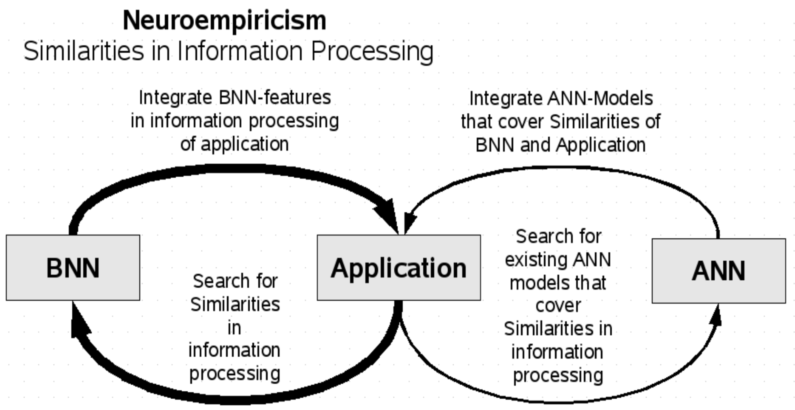

Figure 2: Neuroempiricism and similarities of information processing

In the following section Neuroempiricism is applied to Decision Support Systems (DSS) as the final application that will be developed ([8] Densham & Goodchild in 1989). The similarities of information processing in BNNs and DSSs will lead to a new network topology that extends network topologies usually used for ANNs.

Fuzzy Logic and Spatial Decision Support

As mentioned in the introduction we need a basic data structure that is able to represent a rule based system in a network on one side and operate on spatial domain on the other. First of all we define briefly the basic concept of

Fuzzy Logic and extend that to a spatial input domain $D \subset \mathbb{R}^2$ for representation in SDSS.

Dealing with complex dynamic systems like health care systems a DSS has to process two types of data:

- crisp data (like blood pressure) and
- fuzzy data (like patient descriptions of pain).

Fuzzy data is regarded as a generalization of crisp data by a membership function.
Learning processes and the acquisition of rules in particular cannot be described in a crisp logic manner. For example *"When Peter's hip hurts, he can hardly walk"* is an implication with *"hip hurts"* as the precondition and *"can hardly walk"* as the conclusion. The validity of statements like "*Peter's hip hurts*" cannot be described by mathematical logic with true or false (respectively 1 or 0) values. Therefore Lofti Zadeh [29] suggested in 1965 the extension of the classical two-valued logic to the continuous interval [0,1].

Example: Peter belongs to the fuzzy-set "*hip hurts*" with a grade of 0.8 which means that his hip hurts very much, because the grade is close to 1. If treatment alleviates the pain, Peter's membership to the fuzzy-set is reduced perhaps to 0.2. By extending AND, OR and NOT on fuzzy-sets, rules and fuzzy-implications can be described. Statements like *"IF Peter's hip hurts AND Peter has osteoarthritis AND Peter is NOT taking medicine x THEN apply treatment y"* contain a logical structure operating on fuzzy values.

The output of the Decision Support System (DSS) can also be classified as crisp and fuzzy data. An example for crisp data as output will be: *"Dose of 20 milligrams of medicine x"*. An example of fuzzy output will be: *"choose treatment y with a validity of 0.8"*, which means that treatment *y* can be applied but might have small side effects.

Going back to EWARS as a Spatial DSS we need to apply membership functions to the spatial validity of a fuzzy property and as a consequence the Fuzzy rules and membership functions will operate on an input domain with a location. This implies that the membership functions are representing the validity of a property dependent on the location. To illustrate this we consider two simple properties of SDSS expressed in a membership function:

Now we need to extend the Fuzzy rule so that it operates on an input domain of spatial coordinates. This implies that the membership functions representing the validity of a property is dependent on the location. To illustrate this we consider two simple properties of SDSS expressed in a membership function:

- The risk to be infected by a disease I is high in location $(x, y) \in \mathbb{R}^2$. The membership function $f_t : \mathbb{R}^2 \times V \to [0,1]$ is dependent on the time index $t \in T$.

Remark: f_t is not a density function of a probability distribution. The function f_t changes in time and beside the location f_t is dependent on other parameters too indicated by V (variables). For visualisation we consider the $f_t : \mathbb{R}^2 \to [0,1]$, because the graph of the membership function is a subset of $\mathbb{R}^3$.

For a spatial interpretation of the membership function a visualisation of the graph supports the decision maker in identifying high risk and low risk area. The following surface (see figure 3) is a risk surface generated with a sequence of arbitrary points $P_k \in \mathbb{R}^3$ where $P_k := (x_k, y_k, r_k) \in \mathbb{R}^3$ means that the risk is high with the grade of validity $r_k \in [0,1]$ at location $(x_k, y_k) \in \mathbb{R}^2$.

- For a decision support the visualization of a fuzzy rule system helps the decision maker to interpret a medical risk of infection as a spatial property $r \in [0,1]$ of a location $(x, y) \in \mathbb{R}^2$. Beside the 3D-visualization and surface interpolation of the points $P_k \in \mathbb{R}^3$ the membership function indicates high risk areas $(r=1)$ are indicated by red colour and low risk areas $(r=0)$ are visualized in colour green. Values in between are represented with a smooth transition from red over yellow to green.

- As mentioned in the beginning the network topology of an ANN is weighted directed graph. The points P_k are now considered as pairs of nodes in a network with a weighted edge in between. The weight of the edge is r. One end (node) of the edge is part of the geographical layer with the coordinates $(x, y) \in \mathbb{R}^2$ and the other end is part of the network.

- The generalised topology derived from the BNN enables interfacing different components in a SDSS.

E.g. a learning algorithm of an ANN can train the values r_k which will then modify the membership function for an optimized representation of the spatial property. The indicated index $t \in T$ in the membership function is indicating in this example the modification and optimisation of the membership function $f_{t,v}$.

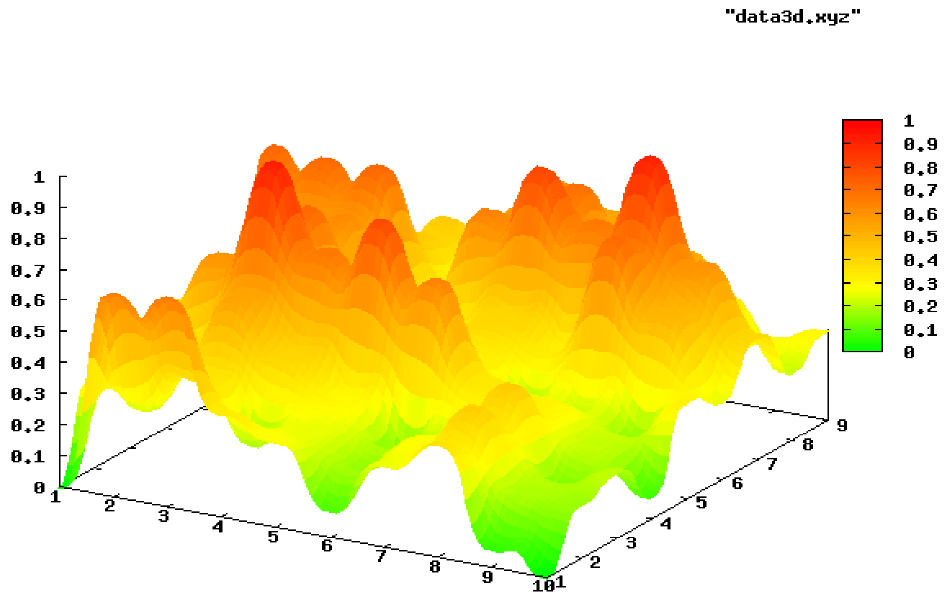

Figure 3: Spatial visualization of a fuzzy membership function $f_{t,v}$ generate by $(P_{1,...}, P_n)$

Fuzzy logic theory can be helpful in modelling decision processes, but the theory will not help in representing the changes in membership functions for fuzzy-sets in space and time. As mentioned in section 1 the complex heterogeneous environment of rural communities is considered as a learning system, so fuzzy-set theory has to be extended to a neuro-fuzzy-system. Artificial Neural Networks (ANN) are used to train the membership functions of fuzzy-sets and vice-versa, fuzzy-rules operating on fuzzy-sets can provide input data and process output data of ANNs.

The neuroempiricism approach has to bridge the gap between rule acquisition in Decision Support Systems and rule acquisition in clinical research in neurophysiology. For example, language learning as described by the neurophysiologists Dale & Christiansen [6] in 2004 and the modelling of Artificial Neural Networks are linked. Rules in mathematics can be found in algebraic equations, geometrical structures or in general mathematical laws. Rules of languages can be described by a formal grammar. Recent studies by Friederici at. al. [21] in 2006 show that the human brain differentiates human and non-human grammar and it is concluded that Broca's area is responsible for processing grammar structure. When a child learns her first language, she acquires rules without explicitly knowing the hidden rules behind the language and without explicit instructions to discover those rules. Breitenstein, C. et al. [2] showed in 2004 that word learning can be achieved without feedback. When a child learns mathematical structures in school, "learning by discovery" is a fundamental principle in mathematics education as described by Winter, H. [20] in 1997. Children have to discover a rule or a mathematical structure behind a sequence of tasks and then they have to describe the structure they have found. Biological Neural Networks (BNN) are able to learn rules by being exposed to a sequence of examples that follow an internal hidden rule. Learning of an ANN and a BNN can be described as a process of approximation.

Pawlak [19] introduced the rough set theory in 1982 as a theory of approximation where indistinguishability of concepts are modelled by upper and lower approximation of concepts. A concept is a non-empty set of examples. In general the rough set theory provides an approach to deal with concepts when only incomplete information is available. Rough set theory and the slightly older fuzzy set theory were combined by Yao [28] in 1997 and Thiele [29] in 1998. A comparative study of Fuzzy Theory and Rough Set Theory was done by Radzikowska and Kerre [21] in 2002. Going back to the learning process of an ANN or a BNN the dimension of "time" has to be added to the process of approximation.

A teacher supports the learning child to find the rule by presenting information and visualisations of different abstraction levels. Mathematical rules can have a formal symbolic structure (like equations) that can be accompanied with additional information of geometrical shapes (e.g. triangle shaped numbers emphasising the symbolic formal structure of the rule, Triangle of Pascal). The abstract rule hidden behind a presented sequence of tasks or a set of mathematical objects are more important in mathematics education than in acquiring rules for languages, because the rule itself is the objective of the mathematical learning processes.

Applying these concepts to the problem of health service delivery, a decision support system is exposed to (i.e. trained with) collected empirical data. The adaptive modules of an ANN in decision support systems should then learn underlying fuzzy-rules facilitating the genesis of appropriate decisions. Going back to introduced setting in rural areas that decisions have to be made independent of existence of EWARS as a SDSS. Even doing nothing decision is made by the decision maker. The decision support should add value to decision making process. But if the SDSS is adaptive then (in addition to the decision support itself) the decision maker needs information of support quality. We consider a finite number of decision options $\{d_{1,...}, d_m\}$ and use two membership function f_t and q_t. If $f_t(d_2)=1$ and $q_t(d_2)=0.03$ - the membership function f_t indicates that for all collected data, the decision option d_2 was helpful and it is also transparent to decision makers that the quality of this decision option is very poor. It is because q_t is indicating that only a few records of data were collected to validate the quality of d_2. The quality property of the decision option can be used to select decision support options that exceed a certain threshold of quality. Neurons in an ANN and BNN have this threshold property defined mathematically by an activation function of the neuron (Rojas [17]). According to figure 1, going back and forth between BNN, ANN and Application, the network topology as a basic data structure in the mathematical model of a DSS is appropriate for this quality aspect as well. For the spatial modelling of risk at the location (x, y) represented by $f_{t,v}(x, y)$ the information on the quality of $f_{t,v}$ at the location (x, y) is given by $q_{t,v}^{(f)}(x, y)$. Now $q_{t,v}^{(f)}$ is a membership itself and can be visualised in a 3D-surface.

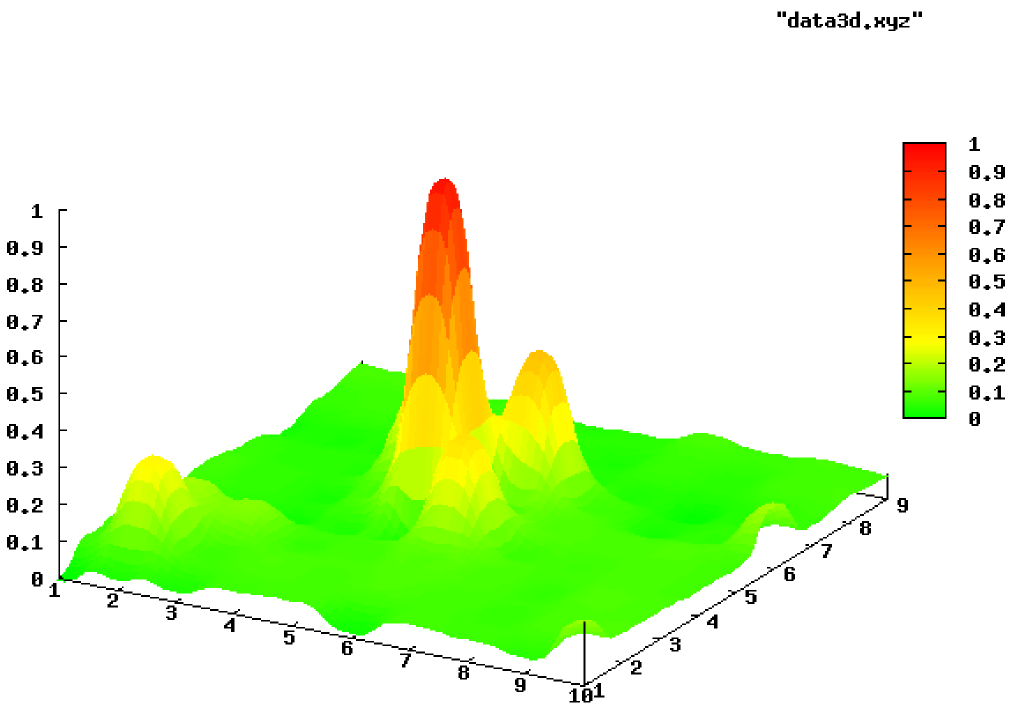

Figure 4: Spatial visualization of a quality membership function $q_{t,v}$

Combine the figures 3 and 4 we have only a small area in SDSS where the quality membership function has a value close to 1 (red parts of the surface). For the decision support it is important for the interpretation of risk in figure 3 if the quality of the information is good. Applying fuzzy-AND on the quality membership function $q_{t,v}$ and the risk mapping $f_{t,v}$ provides a new spatial membership function indicating areas of high risk with high quality of data.

$$\text{AND}(f_{t,v}, q_{t,v}): \mathbb{R}^2 \to [0,1] \qquad (x,y) \to min\{f_{t,v}(x,y), q_{t,v}(x,y)\}$$

For decision support even a poor quality of information can improve the decision making process, because little information on few cases together with the knowledge about the quality is better than no information about the situation. If e.g. only 2 patients out of 10000 people living in an area were tested and both tests were positive (meaning that they are infected with a disease D) then the SDSS can be used to suggest response activities like more testing spatially close to the positive cases, without suggesting to do a public warning on the disease D.

Human beings have to make decisions without having the full insight and knowledge about the situation they are in at a time $t \in T$. The approach of Neuroempiricism transferred on decision support means that the SDSS for EWARS will show spatially quality of data and in turn helps the decision maker to decide where to improve the quality of the data spatially focused on areas with high risk and poor quality.

Furthermore the spatial information on the risk helps to identify, where additional test, vaccination programs or other response measures for a vector are suggested. At this point of the spatial modelling we are at the connection between Early Warning pillar and Response pillar in EWARS.

It can be seen that the methodology behind the development process of ANN-models between risk and response is an associator that maps risk to the available resource. Let $Res := \{R_{1,...}R_k\}$ be a set of *k* different resources. The associator A_t is mapping the location, risk and quality information at location (x, y) to pairs $(r_i, q_i) \in [0,1]^2$ of usability values $r_i \in [0,1]$ and quality values $q_i \in [0,1]$ for the resource $R_{i.}$ Now we are considering "fogging with chemical *C*" as an example for a resource R_1 to eliminate larvae of mosquitoes (Response Support). The usability r_1 of the resource R_1 is dependent on the amount of necessary and available chemicals and the distance to location (x, y) where the chemical *C* is stored. q_1 is telling the decision maker how well the application of the resource R_1 was tested in location $(x, y) \in \mathbb{R}^2$ (e.g. $q_1 = 0.93$ means that fogging with chemical *C* was tested very well for the location $(x, y) \in \mathbb{R}^2$).

$$A_t : \mathbb{R}^2 \times [0,1]^2 \to [0,1]^{2k} \quad (x, y, v_f, v_q) \to ((r_{1,} q_1), (r_{2,} q_2), \ldots, (r_k, q_k))$$

In general the mapping *A* maps a subset of $\mathbb{R}^4$ to a subset of $\mathbb{R}^{2k}$. We consider A as a mathematical function that maps the location $(x, y) \in \mathbb{R}^2$ with the risk value $v_f \in [0,1]$ and quality value $v_q \in [0,1]$ of the risk information to a resource application vector in $[0,1]^{2k.}$ If r_i is close to 1 then the R_i fulfilled e.g. the objective of eliminating larvae of mosquitoes very good. If the quality of data is poor, then not many approved case of chemical application are documented. Any positive application of the resource R_i will improve the quality value q_i and any unsuccessful application R_i will decrease the quality value towards 0.

This implies that the mapping A_t will change during time $t \in T$ just by making decisions that had to made anyway with or without a decision support system. To show the internal structure of the mapping A_t the mathematical function $A_t := M_t \circ D$ is decomposed in a distance function D and a linear associator M_t for which the values of the matrix changing in time indicated by the index $t \in T$.

$$D : \mathbb{R}^2 \times [0,1]^2 \to [0,1]^{k+2} \quad (x, y, v_f, v_q) \to (d_{1,} d_2, \ldots, d_k, v_f, v_q)$$

Every resource R_i has a location $(x_i, y_i) \in \mathbb{R}^2$ and the value $d_i \in [0,1]$ distance between the location and the resource is dependent on the distance between (x, y) and the location of the resource (x_i, y_i). In a homogeneous terrain this could be the Euclidian distance (norm) defined by $\|(x, y)\| := \sqrt{x^2 + y^2}$ and $d_i := \dfrac{1}{1 + c \cdot \|(x, y) - (x_i, y_i)\|^e}$ with $c, e > 0$. If the distance between location (x,y) and the location of the resource (x_i, y_i) is $d_i = 1$ then the accessibility to R_i is very good because no transportation is required. Increasing distance to the resource will make the resource less accessible and the fraction d_i is decreasing. In a network oriented setting (transport setting) the Euclidian distance will be replaced by a network distance because the distance between airports transporting medical equipment might be far in the Euclidian sense but close in terms of the speed in comparison to transportation on crowded roads over a much shorter distance in comparison to the aeroplane. The linear associator, which is linear mapping the distance vector for accessibility

$(d_{1,} d_2, \ldots, d_k, v_f, v_q)$ to the resource application vector $((r_{1,} q_1), (r_{2,} q_2), \ldots, (r_k, q_k))$ is represented by a matrix $M \in Mat(2\mathrm{k} \times (k+2), \mathbb{R})$. The mapping is topologically a directed weighted graph between an input layer with *k+2* nodes and an output layer with *2k* nodes. The components of the matrix column 2 and row 5 is the weight of the edge between the 2nd input node and the 5th output node. This is leading once again to a topological structure of an underlying network. The weights in the network are changing in space in time and need interfaces to other components in the network that change the values in the matrix. Furthermore the fuzzy membership function itself is generated by a network, that is modelling the transport processes of the risk and resources (i.e. epidemiological risk and the medical resources).

Now we examine neurological aspects of decision support and transfer the findings into an extension of neural network models in the mathematical model.

Neural Information Processing and Levels of neural Learning

Schmitz et al. [23] showed in 2001 by physiological, pharmacological, and structural evidence that hippocampal neurons are coupled by axo-axonal junctions, providing a novel mechanism for very fast electrical communication. Artificial neural networks normally have a directed graph as a topological model of biological neural network. Neurons are represented as nodes which act like a computation unit (see Rojas [17]). The directed edges in the graph represent the axo-somal junctions, i.e. the synapse between the axon of one nerve cell (Neuron1) and the dendrite resp. soma of another nerve cell (Neuron2).

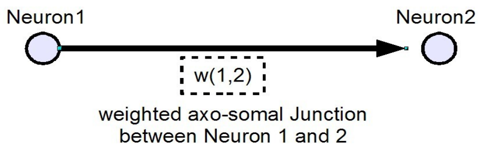

Figure 5: Axo-somal Junction

The junctions are weighted according to excitatory and inhibitory neurons and their synaptic effect on the postsynaptic neuron. Axo-axonal junctions are topologically different from the axo-somal junctions. Transferred into a directed graph it is necessary to introduce directed edges that connect one node with another directed edge. The extension of the mathematical network model yields a new topology in which the modelled action potential of a nerve cell can directly influence the weighted directed edge in the graph.

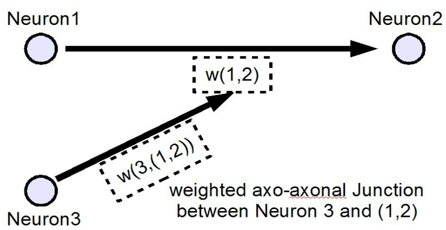

Figure 6: Axo-axonal Junction

According to this extended topology three different levels of learning have to be distinguished:

L1: Impulse processed learning (nerve impulse input for a group of neurons)
Example: The primary visual cortex V1 is regarded as a group of neurons. Visual information from the lateral geniculate nucleus transmitted to V1 will be considered as impulse processed learning, because patterns of impulses are transmitted into a group of neurons. Abstracted to a representation in a directed graph the definition of learning depends on the definition of the considered group of neurons.

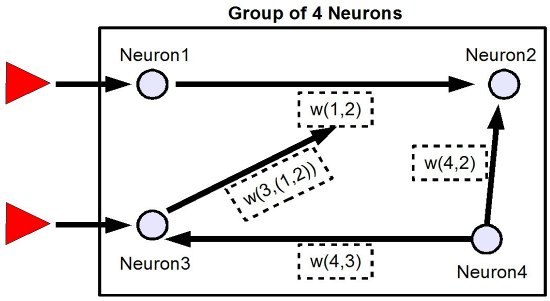

Figure 7: Impulse processed learning

In figure 7 a group of 4 neurons are undergoing impulse processed learning. The input interface is marked by the two triangles. In this example output connections are not considered. The definition of impulse processed learning depends on the selected group of neurons. If we reduce the considered group of neurons to Neuron1 and Neuron2 the smaller group of neurons learns impulses processed from the upper input connection at Neuron1 (triangle)and via the axo-axonal junction *w(3,(1,2))* and the axo-somal junction *w(4,2)*:

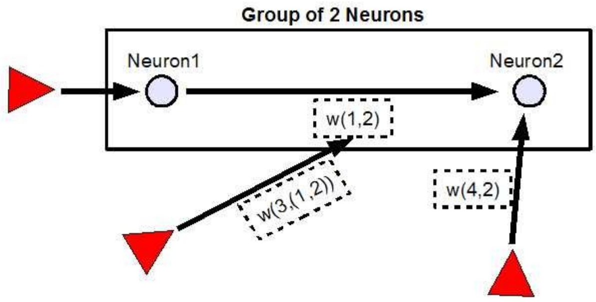

Figure 8: Impulse processed learning in a reduced group of neurons

L2: Parametric learning (changing weights of directed edges or threshold values of neurons),
Example: Changing the weight *w(1,2)* in figure 8 would be considered as parametric learning in a group of 2 neurons.

L3: Topological learning (adding and removing neurons or edges).
Example: The changes from figure 5 to figure 6 are due to two topological learning processes. One is adding neuron 3 and the other is adding the axo-axonal junction between neuron 3 and the directed edge (1,2). Both changes are regarded as topological learning.

Considering rule acquisition for mathematical models the aspect of learning of the neural networks no longer depends on an explicit learning algorithm. The topology itself provides the ability to realise learning on 3 levels with interaction between them. L1 serves as a level of learning, because a nerve impulse is propagated along nerve fibres into a group of neurons (e.g. from retina into the visual cortex). The processing of nerve impulses in a group of neurons can affect parametric learning of L2 by axo-axonal junctions (see fig.8) or by modifying the threshold logic neuron.

The connection between L1, L2 on the one hand and L3 on the other hand can be done by modelling apoptosis (programmed cell death) found in biological neural networks. To every node and every edge an apoptosis value with a threshold logic is attached in a mathematical model. The apoptosis value has an interface to which directed edges can be connected. Propagated nerve impulses can change the apoptosis value by directed edges (L2). The threshold logic of an apoptosis value triggers the programmed death of neurons or the removal of junctions (L3). Linking L1 to L3 impulse processed learning can cause topological changes in the network and vice-versa topological changes affect the processing and propagation of modelled nerve impulses through the network.

Neuroempiricism uses the concepts outlined above to store and process data in analogy to the human brain and to derive decisions directly from the dynamics of data representation in an ANN.

Topology of Fuzzy Rules
As explained in the introduction the generalised network topology
In this section the levels of learning will be applied to fuzzy logical structures. According to the development of an adaptive module and the processing to fuzzy data the fuzzy rules can be represented in a network structure. To illustrate the topological network structure we refer again to the fuzzy statement:

> *"IF Peter's hip hurts AND Peter has osteoarthritis AND Peter is NOT taking medicine x THEN apply treatment y".*

This statement has the following topological structure:

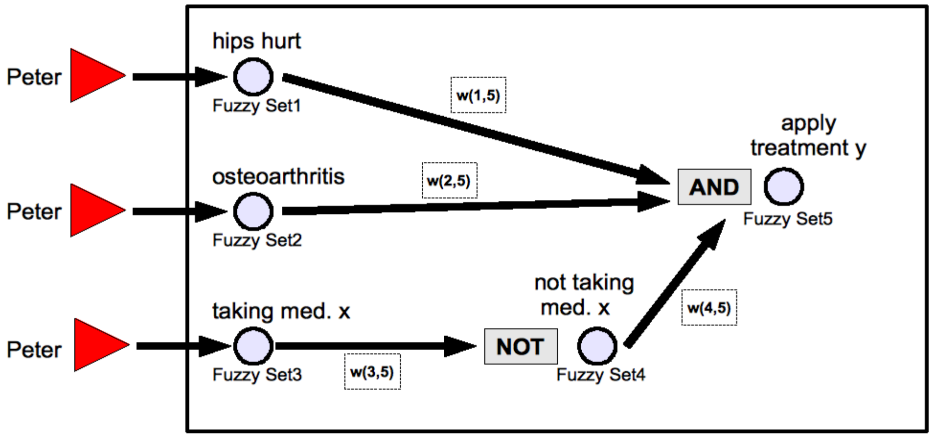

Figure 9: topological structure of fuzzy-rules

The topological structure can learn on level L3 by adding another condition to the given fuzzy implication. The fuzzy sets are connected by AND, OR and NOT. The junctions of the fuzzy logic topology are weighted as in the topology of a neural network learning processes of level L2 can be applied. A convergence of *w(4,5)* towards 0 for example would imply that taking the medicine x will be no longer of relevance for applying the treatment y and in turn if *w(4,5)* increases, there might be more observed side effects of medicine x. This small topological structure will be evaluated for Peter. "Peter" is the input data of the topological structure (L1). The topological structure of fuzzy rules can be evaluated for other patients as well. Every fuzzy set at the nodes will provide a value for "hip hurts", "having osteoarthritis" and "taking medicine x". For every patient the fuzzy set "apply treatment y" suggests the application of treatment y with a certain grade. After applying the treatment y the success is monitored and the monitored data will be used as training data for the topological structure. This can change weights in the network and the definition of the membership functions of the fuzzy-sets itself.

Furthermore, fuzzy logic extends classical logic and is compatible with it. The fuzzy set "taking medicine x" can be interpreted as a crisp way by classical logic. "Taking medicine" can be true (with a grade of 1) or false (with a grade of 0). It makes sense to extend this crisp value to a fuzzy logic representation. For example if a patient has stopped taking the medicine x just one week ago, it is possible to model it by a grade less than 1. The value depends on the amount of medicine x which is still remaining in the body of the patient.

Transferred to the spatial environment the application of treatment X needs medical resources and the creates a demand that has to be covered by the available resource.

Network layers and spatial problems

Next, let us consider two examples of spatial problems related to health care – the dissemination of a viral infection and the optimal distribution of medical goods and services in a healthcare system. We have to consider different dissemination layers of propagation routes of a virus or logistical routes of medical goods and services according to the risk. Layers are mapped and connected to each other, because medical goods and services have to be distributed depending on the risk assessment and the routes of spread of a virus. Unsupervised learning algorithms used by Kohonen-networks [15] create a mapping between the input space and a network layer. The input data reorganises the mapping without a teacher "who is telling" the ANN whether it has produced correct or false output. In contrast to unsupervised learning, supervised learning algorithms like back propagation (see Rojas

[17] 1996, pp.149-171) focus on error reduction of the ANN. The main difference is that Kohonen-networks reorganise the mapping by getting input data without evaluating an error measure for the learning processes. Kohonen-networks (see Rojas [17], pp.389-410) create with their topology a neighbourhood preserving mapping. The model is derived from the human brain by mapping the body's sensory surface to the representing areas in the brain. The size of these areas are typically linked to the importance of the sensory surface. For example the fingertips have a bigger area of representation than a spot on the arm with the same geometrical size. Therefore, Kohonen networks can be trained to detect areas of importance for the information processing in the DSS. Furthermore medical problems have spatial aspects particularly when focussing on epidemiological problems such as virus dissemination models. According to the Kohonen model we can have the earth surface with available data of the specific viral infection cases under consideration (e.g. in a Geographical Information System=GIS). The property of a neighbourhood preserving mapping of an ANN is in this case relevant, because infected patients can infect others according to spatial or epidemiological distance to other people. The adaptiveness of Kohonen-networks leads to a useful visual representation of the data (technically called a chart of the input space) by mapping the earth surface to the representing areas of the ANN. The Kohonen-network is self-organising based on the importance of the input area and its output is ultimately the trained network itself. By next applying stochastic networks to the trained Kohonen-network, the transmission to other areas can be modelled spatially by probabilities (dissemination model).

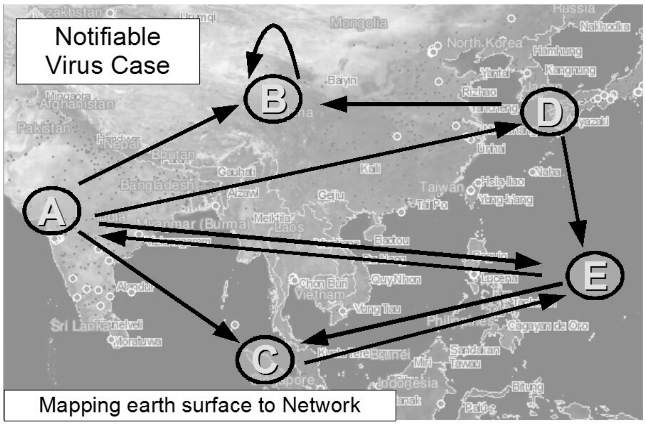

Figure :10 Topology and neighbourhood preserving Kohonen-network

In figure 10 you will find the two layers: 1) The layer of geo-spatial data (represented by the earth surface) and 2) the layer of the Kohonen-network mapped to the earth surface. Operation in the network layer that preserves the original spatial topology is used to do spatial analysis in the output area of the Kohonen-mapping. Kohonen-networks chart the input space but will not model the dissemination of the virus. Representing dissemination rules in a network by applying Fuzzy Logic or stochastic modelling the layer of the Kohonen-network will be the input for the fuzzy rule layer. Bridging the gap between artificial learning in an extended network model and the complex notion of deciding by rules in a neurological environment is related to findings in rule acquisition in languages. Artificial grammar learning examined by Breitenstein & Knecht [3] in 2002 and mathematical models of rule acquisition focus on the notion of representing the rule in computational decision models.

Sejnowki and Rosenberg [22] described in 1986 the construction of a speech synthesis software by applying a backpropagation ANN. For the neural network called NETtalk the rules for speech synthesis were not implemented, but it was trained by supervised learning. The authors stated NETtalk made the same errors as children when they learn their first language. Furthermore the authors determined groups of neurons that implicitly learned known linguistic rules.

3 Discussion

This article addresses the basic concept of applying the principle of Neuroempiricism to tackle medical problems. Medical findings in neurosciences and information processing in the human brain return to medical informatics and mathematical modelling by applying these concepts of Artificial Neural Networks. An abstraction of joint concepts and the adaptation to ANN-models can be found in Fuzzy Logic and learning models of network topology itself. ANN-modules in computer based decision support systems can be improved by integrating the concepts of topological and parametric learning in an underlying single ANN-model for rule acquisition for spatial risk mapping and distribution of medical resources. The complexity of the considered healthcare systems implies the application of adaptive strategies for decision support. Modelling the interface between ANN, for which the output of one network modifies the weights of other ANN (as directed weighted graphs) in the decision support system needs an extended underlying network structure.

Axo-axonal junctions can be found in neural information processing of BNNs. Transferring this to an artificial topology we have to extend the artificial neural topology with axo-axonal junctions, too (as shown in figure 6). The objective is to acquire a unified generalized topology by supervised and unsupervised learning processes for decision support concepts with modelled levels L1, L2 and L3 (see section 2). This is necessary for a fault tolerant dynamic model of a decision support system that can be used with or without instruction, and respectively with or without feedback (i.e. training data).

The new extended network model is not equivalent to topologies normally used as directed and weighted graphs in an ANN. For example, a fully connected topology with 2 neurons has normally 4 directed connections whereas a fully connected extended network with 2 neurons and axo-axonal connections has an infinite number of directed connections.

With the extended generalized topology axo-axonal junctions can be used to modify weights of fuzzy rules or weights in an ANN. Conversely, an ANN or a network of fuzzy rules can modify weights in a network structure. The result is that fuzzy rules, rough set models and classical ANN topologies can communicate within a unified network structure. The models generate spatial rules of logistical or epidemiological distance that are not visible in the original spatial layer where the data was collected. Adaptiveness keeps a DSS responsive to changes in the health risk maps and the logistical distribution of medical goods and services. The axo-axonal topology provides the ability to model the changing validity of an expert rule by collected data. In general the concept of Neuroempiricism applies medical findings in neurosciences to mathematical modelling, so that biological properties of neural systems can be translated for beneficial use in medical informatics and medical problems of modelling. Using the new extended topology enables the representation of spatial problems such as virus propogation and the spatial dissemination of medical goods and services according to the dynamics of medical demands.

4 Conclusion

It is evident from the above examples, figures and discussions that it is imperative to a have a network topology which depicts how the BNN provides an extension of the ANN so that both fuzzy and crisp data can be processed in a unified network typology. This is a unique and new way of focussing on the BNN and ANN as the information interchange between fuzzy and neural networks are not usually incorporated into a joint network topology. The distinctive element of the topology arises as the axo-axonal connections are not typically modelled in an artificial neural network. The connection between DSS and neural networks is to make the DSS adaptive to the environment of the rural communities because the neural network is able to learn by processing collected data and also then fuzzy rules have the ability to learn.

The next step will be the application of mathematical measure theory to the unified generalised network model that is able to represent axo-axonal junctions derived from the BNN. This is necessary to check and test convergence of the Decision Support System according to its supported decisions as well as the feedback to these decisions, amidst the demands, functions and constraints of health service delivery. The measure theory applied on the extended network should not be an external evaluation of the DSS. Error measures and error correction will be represented as a part of the generalized network topology that will modify the network by the three levels of learning mentioned in section 3 (e.g. modify weights in Fuzzy rules or weights in an ANN topology by axo-axonal junctions according to an error measure). The extended topology should be defined and standardised in an XML-based format, so that trained risk maps and efficient distribution strategies of medical goods and services according to the risk can be imported and exported to different support systems in a complex health service system that represents spatially risk cover of resources according to risk and the spatial quality of the available information.

List of Abbreviation

- ANN Artificial Neural Network
- BNN Biological Neural Network
- DSS Decision Support System
- SDSS Spatial Decision Support System
- XML eXtensible Markup Language

Authors' contribution

EN develop the mathematical spatial modelling, MH made substantial contributions on decision making for health service delivery in rural areas. AB revised the paper critically for important intellectual content.

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