Managing Innovation and Diversity in Knowledge Society Through Turbulent Time
25–27 May 2016
Timisoara • Romania

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TIIM

Management, Knowledge and Learning
Joint International Conference 2016
Technology, Innovation and Industrial Management

KNOWLEDGE EXTRACTION AND ADVANCED ANALYSES THROUGH INVERSE MODELLING USING ARTIFICIAL NEURAL NETWORKS

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Abstract:
Using artificial neural networks (ANN) to model an observed process is state of the art in engineering and is receiving more and more attention in social or marketing research. As shown in previous publications static data analytics, like an ANN based dependency matrix (DM), creates a better understanding of the relationship between dependant and independent variables of the observed system. To gain a better understanding of the behaviour and dynamics of an observed system a further step has been taken. . This is accomplished by transforming the ANN-DM into its open form equivalent. This is represented by several ANN models, one for each observed model parameter. An algorithm, which was published by the author, can be used for this transformation. The final result makes it possible to study the dynamic relationships between all parameters, including simulation and conclusions on its inverted model behaviour. The author will show based on an example from tourism marketing, how this inverse modelling approach can be applied and what new knowledge can be extracted from the achieved simulation results. The conclusion is that ANN based algorithms makes it possible to model an observed system in a static but also in a dynamic way. Inverting the model generates a deeper insight view and additional knowledge about an observed system. The resulting applications range from supporting strategic decisions to predictive control or model based simulation.

Keywords: knowledge extraction, model inversion, artificial neural networks, decision support systems, simulation

1. APPLICATION BACKGROUND

The following article uses former marketing research work, done a few years ago to study the relationship between touristic regions and its customers. This research work is explained in more detail in (Stöckl& Rinke, 2015). A summary of the publication is presented to give a better understanding of this research background. Tourism experiences in viticultural areas tend to evoke strong positive and affective consumer reactions (Yuan et al., 2008). Ideally they lead to sentiments such as pleasure, satisfaction, nostalgia, or even emotional attachment (Gross & Brown, 2006; Hammitt, Backlund, & Bixler, 2006). Studies show that satisfaction is strongly related to attachment to a certain place (Williams & Huffman, 1986) and pleasure (Orth et al., 2011) and can lead to consumer loyalty (Dodd, 2000; Alexandris, Kouthouris & Meligdis, 2006) as well as greater spending (Moore & Graefe 1994; Dodd, 2000; Kyle, Absher & Graefe, 2003). In addition, research showed that visitors who are familiar with a region, i.e., they have visited the destination before, are more likely to develop strong attachment to that place over time (Williams, Patterson & Roggenbuck 1992).

1.1. Parameters used within the model

Low and Altman (1992) identified four key elements which underlie the theory of place attachment: Firstly, that affect, emotion and feeling play a critical role in the concept of place attachment. Secondly, that environments and settings can indeed vary in several important ways with varying degrees of attachment by people. Thirdly, that families and members of communities, and entire cultures collectively can share attachment to a place. Finally, that attachment to a place is influenced by temporal variations.

The specific factors which may or may not lead to attachment such as perceived crowding (Kyle et al., 2004), involvement (Hwang et al., 2005), shared values (Park et al., 2013), or level of specialisation (Bricker & Kerstetter, 2000) are numerous and vary from author to author across the different studies in the extant body of current literature. Whilst in most of the studies relations among the variables were successfully established, Kyle et al. (2004) propose that further research is necessary in order for researchers to have a better understanding of the development of attachment factors in tourism, its antecedents and behavioural outcomes. Earlier research on this topic particularly investigates short-term effects of affective reactions to a tourism experience. Brakus, Schmitt, & Zarantonello (2009) point out, however, that the stimulus may extend far beyond short-term impacts such as spending. Therefore, long-term customer relationships i.e. attachment and loyalty have to be investigated more closely, especially with respect to the interrelationships among influencing factors.

1.2. Data collection

More than 3,200 tourists from 14 tourism destinations in seven countries were interviewed. After an initial explorative factor analysis data mining techniques, namely ANNs were applied in order to detect interdependencies between independent variables. The basis consisted of 36 variables derived from existing literature and including factors such as *service quality,* (*beauty of) landscape, (high) standard of living, (level of) child-friendliness*, *possibilities to broaden one's horizon, the perceived price-quality ratio* and *trustworthiness.* The questionnaire for our empirical study, that was used to collect the data set, consisted of a total of 57 questions including ratings of the wine tourism destinations' characteristics (influencing factors) on 7-point Likert scales. Validated item batteries derived from existing literature and concerning pleasure and emotional attachment were used to assess wine tourists' affections.

2. STATIC MODELLING

The technology used for modelling the survey data is based on artificial neural networks (ANN). So far, regression analyses including mediator and/or moderator relationship tests were applied in the majority of studies. There are, however, certain limitations of these techniques that have been noted in the literature. Additionally, artificial neural networks ANNs have an advantage over multivariable logistic regression analysis when it comes to the differentiation of influencing factors as well as in the standardisation of interrelationships between variables. Specifically, ANN models significantly outperform multivariable logistic regression models in both senses of discrimination and calibration (Eftekhar et al., 2005).

2.1. Dependent and independent parameters found in the study

In an initial exploratory factor analysis and a cut-off at a Cronbach's Alpha value <0.7 seven (of 35) remaining items were identified, automatically grouped (loading on one factor) and taken into further analysis with ANNs. The remaining and therefore most influencing variables are: *familiarity*; the *human factor*; *trustworthiness*; *the offer of leisure activities; relish*; *child-orientation* and *opportunity to broaden one's horizon.*

Dependent variables investigated are: *Pleasure, emotional attachment, satisfaction, loyalty* and *spending*. Both independent variables (regional attachment factors) and dependent variables (affective tourist reactions) as well as referenced questions are shown in table 1.

Table 1: Model parameters and original questionnaire numbers

Description	Referenced Questions
Regional Attachment Factors (independent parameters)	7-point Likert scales
familiarity	How well do you know the XY wine region? (This is my first visit – I come here regularly) (v101)
human factor	Average value of: service staff and tourism personnel take excellent care of their customers (v103); people are friendly and excellent hosts (v116); people are trustworthy and reliable (v118)
trustworthiness	Concentrating on exploiting tourists rather than on providing true value (v129)
leisure activity	A wide range of leisure and sport activities are offered (v112)
relish	Average value of "without peer for fine wining and dining" (v123); "exactly THE place to drink superb wines" (v124)
child-orientation	Ideal for children (v131)
broaden horizon	An ideal place to broaden one's horizon (v136)
Affective Tourist Reactions (dependent parameters)	7-point Likert scales except for spending
pleasure	Average value of : happy – unhappy (v138); pleased – annoyed (v139)
emotional attachment	Average value of: feel strongly attached to the XY region (v152); I am strongly emotionally connected to XY (v153); I do NOT feel any emotional bond towards XY (inverse item) (v154)
satisfaction	Average value of: highly satisfactory – highly unsatisfactory (v144); very pleasant – very unpleasant (v145); terrible – delightful (inverse item) (v146)
loyalty	Average value of: am willing "to go the extra mile" to get here (v148); I can highly recommend a visit here to relatives and friends (v149); will come back here in the future for holidays (v150)
spending	Average value of: Estimated tourist spending to the XY region on average (v155) – own spending (v156)

Source: (Stöckl A., Rinke W., Eisingerich A., 2015)

2.2. Generated dependency matrix DM for the derived model

To get a comparable insight view of the built model with respect to the value ranges, we calculate the dependency matrix DM (Rinke W., 2015 May). The resulting table tell us how strong a certain independent parameter influences a dependent parameter. The results can be seen in table 3.

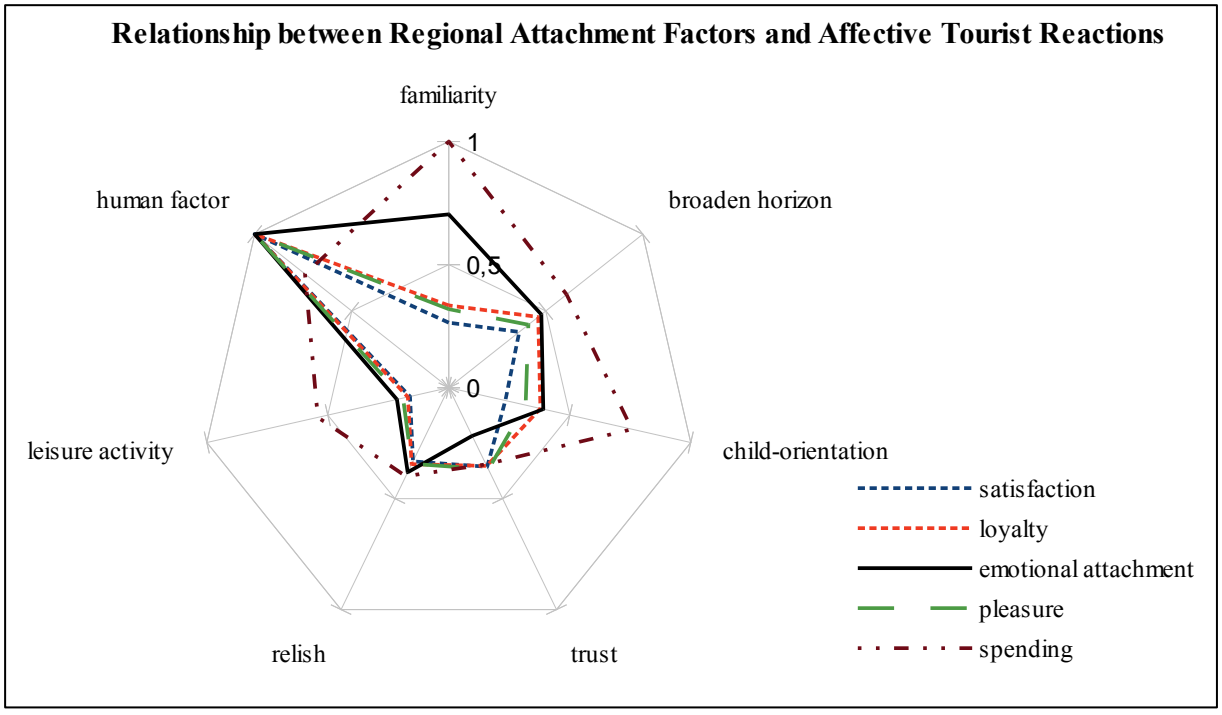
Table 2: Dependency Matrix for the derived model

Dependency Matrix	satisfaction	loyalty	emotional attachment	pleasure	spending
familiarity	0,26	0,33	0,70	0,32	1,00
human factor	1,00	1,00	1,00	1,00	0,74
leisureactivity	0,16	0,17	0,21	0,19	0,54
relish	0,33	0,34	0,38	0,34	0,40
trust	0,36	0,35	0,22	0,37	0,35
child-oriented	0,23	0,38	0,39	0,32	0,76
broaden horizon	0,36	0,46	0,48	0,41	0,61

Source: (Stöckl A., Rinke W., Eisingerich A., 2015)

The following spider web diagram (picture *1*), visualises the relationship between the independent and dependant variables of the static model in a graphical form.

Picture 1: The dependency matrix shown in table 2 is shown as spider web diagram



Source: (Stöckl A., Rinke W., Eisingerich A., 2015)

Key findings derived from the dependency matrix and with regard to the generated model show that the *human factor* (people) has the highest influence on affective wine tourists' reactions. *pleasure, satisfaction, emotional attachment* as well as *loyalty*. Scale values in *familiarity* as well as the *human factor* and *child orientation* are highly related to the response behaviour regarding *spending*.

3. DYNAMIC MODELLING

The benefit of generating an ANN model from the observed system is not only a nonlinear static model generated by calculating the dependency matrix but also the added bonus of using the same basic

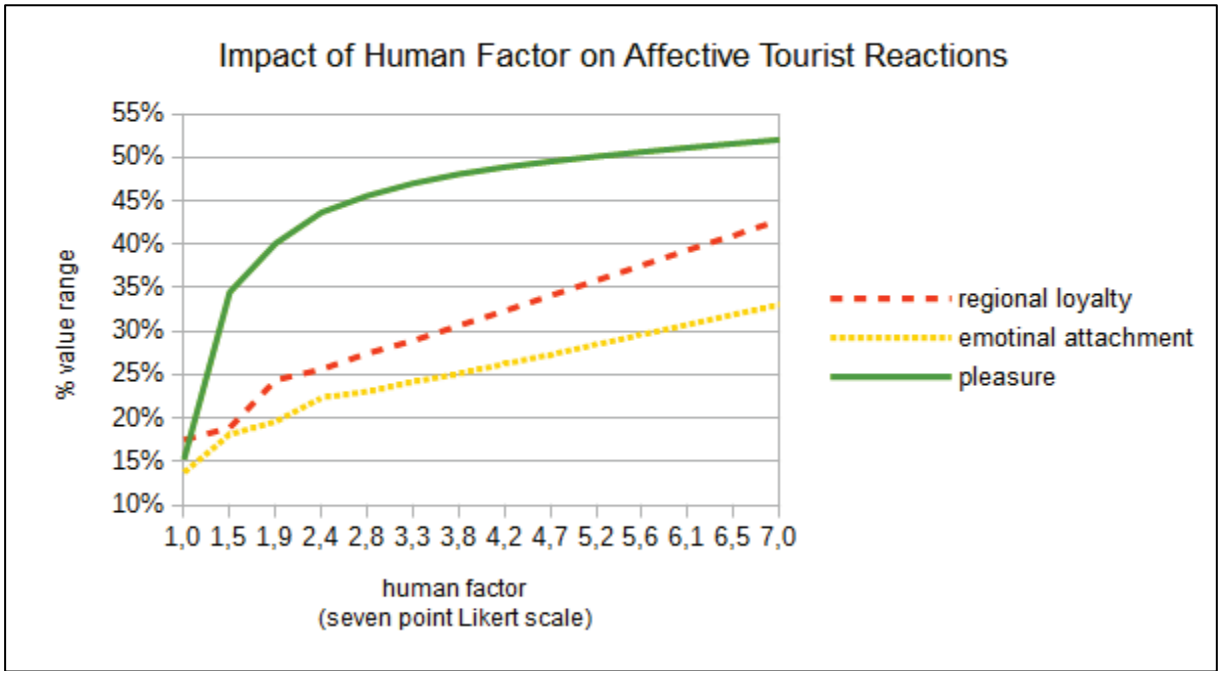
ANN model to study the dynamics between the observed model parameters. Feed forward simulations allow to study the dynamic impact of independent variables on the observed dependent variables.

3.1. Feed forward simulation

To run a feedforward simulation with an ANN is a simple process by changing the input vector of the ANN and evaluating the output vector as a result. The values in the output vector represent the expected impact on the dependent variables. The simulation is done by changing the value of one independent parameter over its value range and collecting the simulation results. In the presented marketing research application, the feed forward simulation was used to collect knowledge about the nonlinear dynamics and how strong dependent parameters are effected by one single independent parameter. This way all possible questions on analysing how far an independent variable must be changed, to have a (significant) positive impact on the *affective tourist reaction* can be analysed and answered. The findings from the static model calculations can be confirmed and are seen in the simulation runs, although the findings are more detailed and nonlinear.

From the simulation results as shown in picture 2 we can see, that the tourists' ratings of the local people (*human factor*) have a significant impact on *loyalty* and *emotional attachment*. The relationship is close to linear and any improvement of the *human factor* improves *loyalty* to the visited wine tourism region along with *emotional attachment*. The strongest affective reaction can be seen on the parameter *pleasure*. This relationship is nonlinear. The strongest improvement can be achieved, when the evaluation of the *human factor* is raised from 0% to 15%. This step leads to an improvement of 25% in *pleasure*. This means that a certain minimum level for the *human factor* is obligatory in order to gain a medium or a good level of *pleasure*. Further improvement of the *human factor* can improve the tourism region's *pleasure* performance by another 10-12% of its value range.

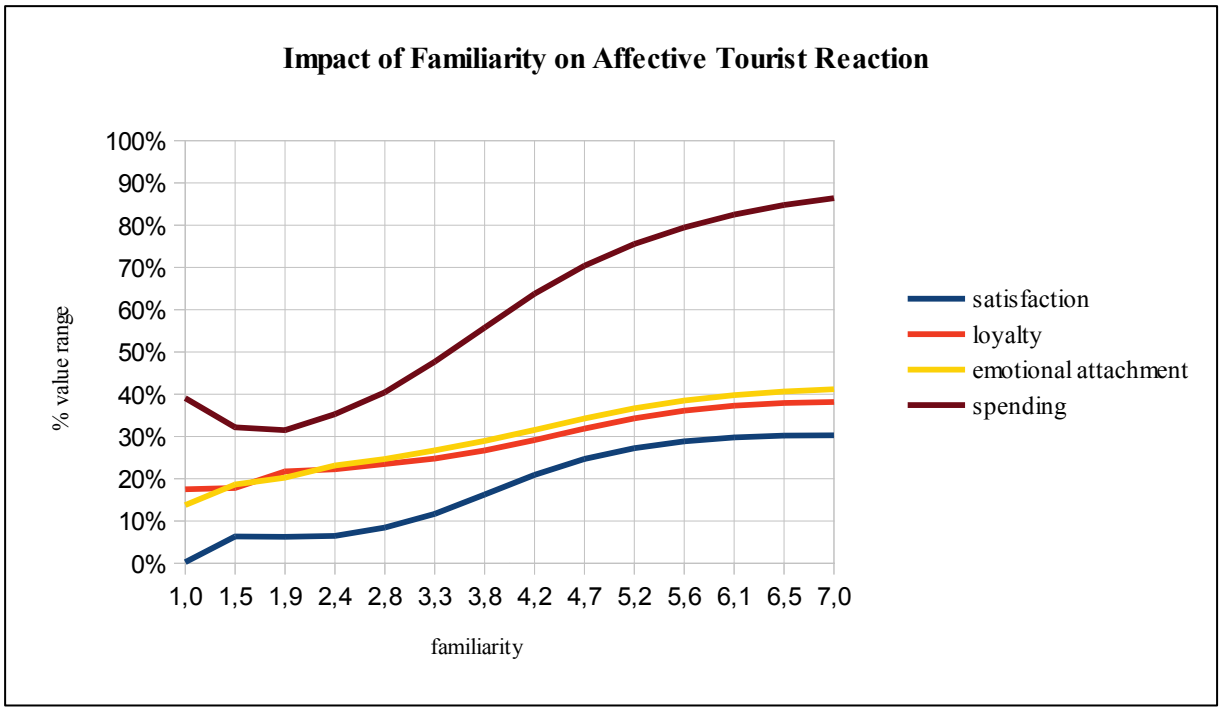
Picture2: Influence of human factor on affective tourist reactions



Source: (Stöckl A., Rinke W., Eisingerich A., 2015)

Another important parameter in our research study is *familiarity* because it shows a strong positive correlation with the parameter *spending,* which is one of the parameters that describes affective tourist reaction.

Picture 3: Influence of familiarity on affective tourist reaction



Source: (Stöckl A., Rinke W., Eisingerich A., 2015)

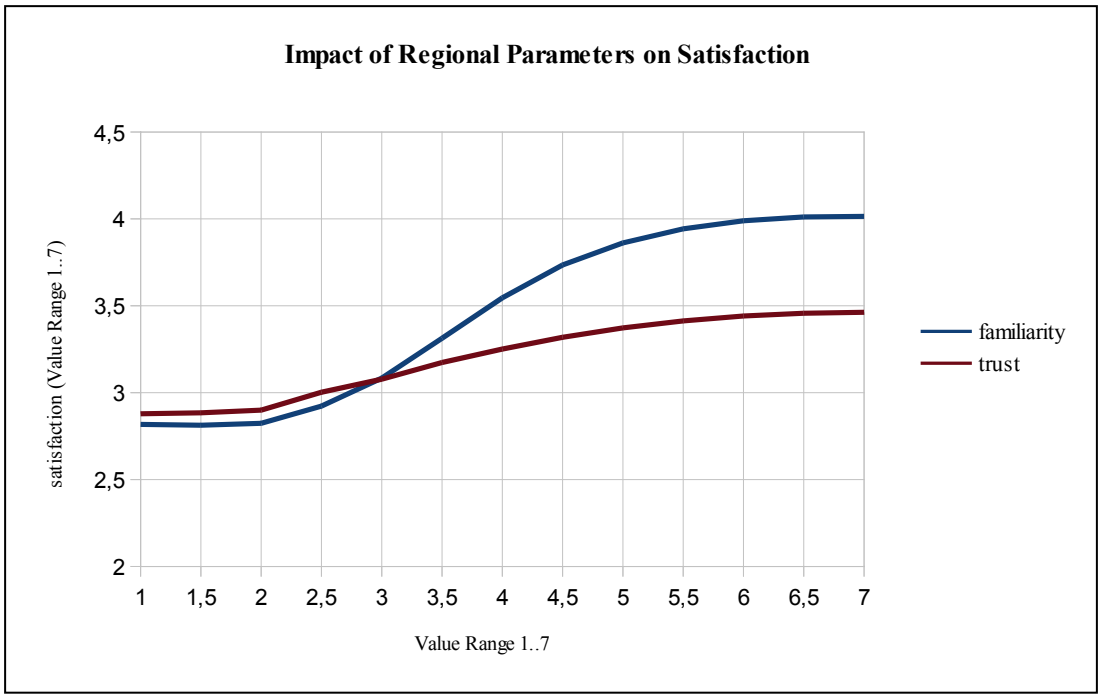
In picture 3 you can see this relationship. A value increase from 2 to 6 can increase the parameter *spending* by about 50% of its value range. At the same time the parameter *satisfaction* can be increased by about 25% and the parameters loyalty and emotional attachment are also increased by about 20% of their value range respectively.

3.2. Inverse model simulation

The next level of knowledge extraction from model simulation can be achieved through inverting the ANN model into its open equation form representation. This conversion can be performed with the algorithm described in the author's conference paper. (Rinke W., 2015 June) Inverse model simulation is a powerful technique used in advanced process control and optimisation applications. In social and marketing research it provides the tools to answer strategic questions, to learn about the necessary changes on the dependant variables to achieve a certain target value. A typical scenario in tourism is to know, how much improvement has to be achieved on which independent variables to reach a certain goal.

Two examples from the marketing research demonstrate benefit of inverse model simulation. The parameter *satisfaction,* as shown in picture 4, is significantly influenced by two parameters *familiarity* and *trust*.

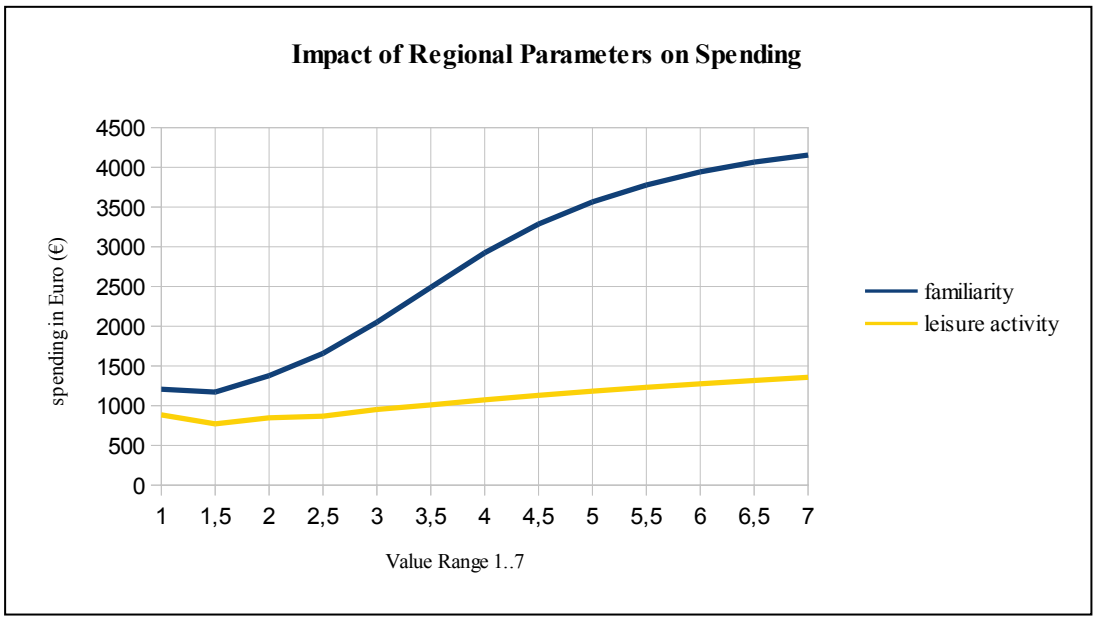
Picture 4: Parameter "Satisfaction"



Source: (Stöckl A., Rinke W., Eisingerich A., 2015)

The simulation results show that the parameter *satisfaction* has the strongest effect in its value range between 3 and 5. Which means that to increase the value for the parameter *satisfaction* up to a level of 4 on Likert scale, the parameter *familiarity* should be between 4 and 5. Above a value of 5 the effect is minor and not noticeable on the Likert scale. The parameter *trust* is most effective in the range of 2 to 6 and increases the value for the parameter *satisfaction* by about 10% of its value range.

Picture 5: Parameter "Spending"



Source: (Stöckl A., Rinke W., Eisingerich A., 2015)

Looking at the parameter *spending* as shown in picture 5 above, the parameter *familiarity* has the biggest impact. Another result is that the parameter leisure activity has an increasing effect on the parameter spending, which can be seen from the simulation.

4. CONCLUSION

As you could see from the different modelling techniques, static and dynamic modelling generates different knowledge and insight view on the observed system or subject. A static analysis in terms of calculating the dependency matrix of the trained network, gives information about the relative importance between dependent and independent model parameters. The mathematics behind the calculation of the dependency matrix can be found in detail at (Rinke W., 2015 May). The model used for analyses is a traditional feedforward perceptron model with one hidden layer. The backpropagation learning algorithm is used for training the model. The dynamic analysis is done with the same model, by varying each of the independent parameters over its value range and observe the functional behaviour of the dependent variables of the model. Typical results you can see in picture 2 and 3 above, for example. The knowledge you gain from the feedforward simulation helps to learn about the model dynamics. Not all parameters of variables have the same impact over the value range. Some variables have a strong impact at lower values, others in the upper range or in the middle value range. All these transfer functions are highly nonlinear, and difficult to model in a traditional sense. With this approach we can answer questions about how do dependent variables change, when a single independent variables value is changed in a certain way. Finally, the third method is inverting the original feedforward model into is open equation equivalent form. This is explained in more detail in (Rinke W., 2015 June). Running simulations with the open equation form model or inverse model let us learn how to optimize the observed system. It transforms a simple feedforward model into a decision support system to optimize the observed subject. If you are interested to know, what parameter you need to change and how big the change has to be to reach a certain goal, the inverse model simulation gives you an immediate answer to this question. Examples for such simulation runs you have seen in picture 4 and 5 above. So finally each of the described approaches generates different knowledge about an observed system.

Artificial neural network (ANN) analysis has been argued to overcome some of the shortcomings of general and widely applied regression analyses. Despite its noted strengths social and marketing researchers are still hesitant to employ artificial neural network analyses. In our research, we therefore aimed to use artificial neural network to demonstrate the critical role it can play in informing research and marketing practice. Especially the application of powerful algorithms like ANN model inversion and the calculation of the dependency matrix allows the analyses of nonlinear complex systems more efficiently than traditional statistical methods. We acknowledge that this research is a motivation and we invite future researchers to use artificial neural network analyses as part of their research efforts.

Comparing simple regression analyses with the methodology of artificial neural networks you have to look at how both techniques are used. Regression analyses try to fit well known linear or nonlinear functions to a data set, by minimizing a certain cost function. Multilayer feedforward artificial neural networks are universal approximations and the type of function you try to fit to your data set is a priori unknown. The only things you know about your observed system are the input data and related output data. Cybenko (1989) and Hornik et al. (1989) proved that any continuous mapping over a compact domain can be approximated as accurately as necessary by a feedforward neural network with one hidden layer (Omidvar, 1997). This is impossible with traditional regression methods. Based on the theoretical findings, multilayer ANN allow one to build robust observation models and to use them for system identification for almost any kind of observable systems. Artificial neural networks can efficiently approximate and interpolate multivariate data and are well accepted for nonlinear statistical fitting and prediction (“ridge regression”) (Omidvar, 1997). Consumer emotions, feelings and affections as well as regional aspects can be considered as typical nonlinear. Whenever the mathematical relationship between all the different observed parameters and its values, that have been collected for the observed system are unknown, traditional regression methods for model building are insufficient. Therefore, we considered using the proper technologies – artificial neural networks, dependency matrix and model inversion in order to identify the unknown relationships between independent and dependent parameters.

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