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1 Introduction

Planning is concerned with a deliberate set of actions aimed at improvements in future qualities that would not otherwise be realized within a given time. This description indicates that 'the future' is a key concept in planning. However, the word 'qualities' also implies that the future is not an objective reality but rather a subjective construction. Evidently, each person has his or her own interpretation of the meaning of 'good quality'. A forecast is a statement about future conditions and therefore is always arbitrary, rather than being 'a statement of fact'.
The term 'forecasting' is often used for both quantitative predictions of future developments and for qualitative explorations of possible futures (Armstrong, 1985; Makridakis et al., 1998; Pourahmadi, 2001). In this paper we will discuss both types of forecasts and their use in environmental and infrastructure planning.

2 Qualitative forecasting

Qualitative forecasting methods principally rely on personal judgements to generate forecasts. These methods consist of guidelines or procedures for gathering the opinions of experts, stakeholders or other interested parties. Qualitative methods can be used when one or more of the following conditions occur:

- There is little or no historical data on the variables to be forecast
- The relevant environment is likely to be unstable during the forecast horizon
- The forecast has a long time horizon, that is, five years or more.

The two most popular qualitative approaches will be briefly discussed here: the ‘Delphi method’ and the ‘Scenario’ approach.

2.1 Delphi method

An interactively structured collection of anonymous opinions is often called a Delphi method (Sackman, 1975; Kenis, 1995). The anonymous exchange of opinions is the most important characteristic of a Delphi approach, as in a group setting opinions can be influenced by many things, including the dominant positions of some participants, personal characteristics and ‘alleged expertise’. It is less meaningful to strive for a consensus forecast by just putting all the experts in a room and letting them ‘argue it out’. This method falls short because those individuals with the best group interaction and persuasion skills often control the situation.

The Delphi method was originally developed in the 1950s by the RAND Corporation, a US Intelligence think tank. It had its greatest triumphs in the 1960s and 1970s (Linstone and Turoff, 1975). However, in the last decade we have seen a strong revival due to, among others reasons, modern computer techniques for organizing such brainstorming sessions in a network setting, so-called ‘groupware’. At present, many consulting firms have their own approach to structured brainstorming and, of course, their own ‘trade name’. Evidently, recent interest in collaborative approaches and consensus planning is another important reason for the application of this method (Woltjer, 2000).

The basic structure of a procedure according to the Delphi method is as follows:

1. The selection of participants.
2. An initial set of questions sent to all participants. For example, in the case of a forecast they can be asked for estimates of certain variables at a future time, for the likelihood that these estimates will be realized, for minimum and maximum estimates, and last but not least, the *reasons* for these estimates.
3. The co-ordinator, or computer program, then tabulates or summarizes the outcomes into, for example, expected or average figures.
4. Results are then returned to each participant along with anonymous statements and they are asked to review their earlier opinion.

5. The process continues until little or no change occurs. The end result may then be seen as a consensus solution.

A strong point of this approach is that it can be applied under many circumstances since it is not strictly dependent on a priori information. A brief fact sheet, a long report or a presentation of the problem under consideration may, of course, benefit the thinking of participants, but the original idea is that each participant enters the procedure with only his or her own basic knowledge. The process of the group creation of judgmental forecasts is largely one of reasoning and argumentation. These reasons and justifications underpinning the forecast may be crucial in persuading outsiders to accept the outcomes. A weak point is that the final result will always depend on the people who are invited to participate, on their ability to think along the lines required and to express themselves clearly. Also, a consensus solution may give a false idea of 'certainty', but in planning, 'consensus' usually has a much higher priority than attempting to predict certainty in a future that is intrinsically uncertain.

2.2 Scenario approach

Wiener and Kahn (1967) introduced the notion 'scenario' in their book 'The Year 2000'. A scenario is a narrative forecast that describes a potential course of events. It should recognize the interrelationships of system components. A scenario is a "script" for defining a possible future including likely impacts on the other components and the system as a whole.

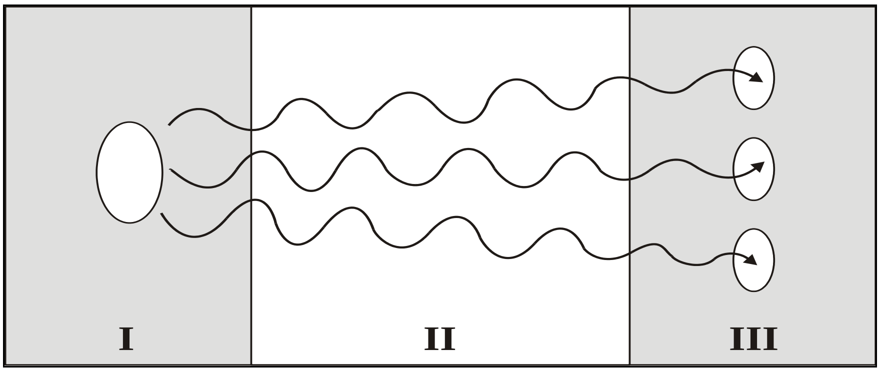


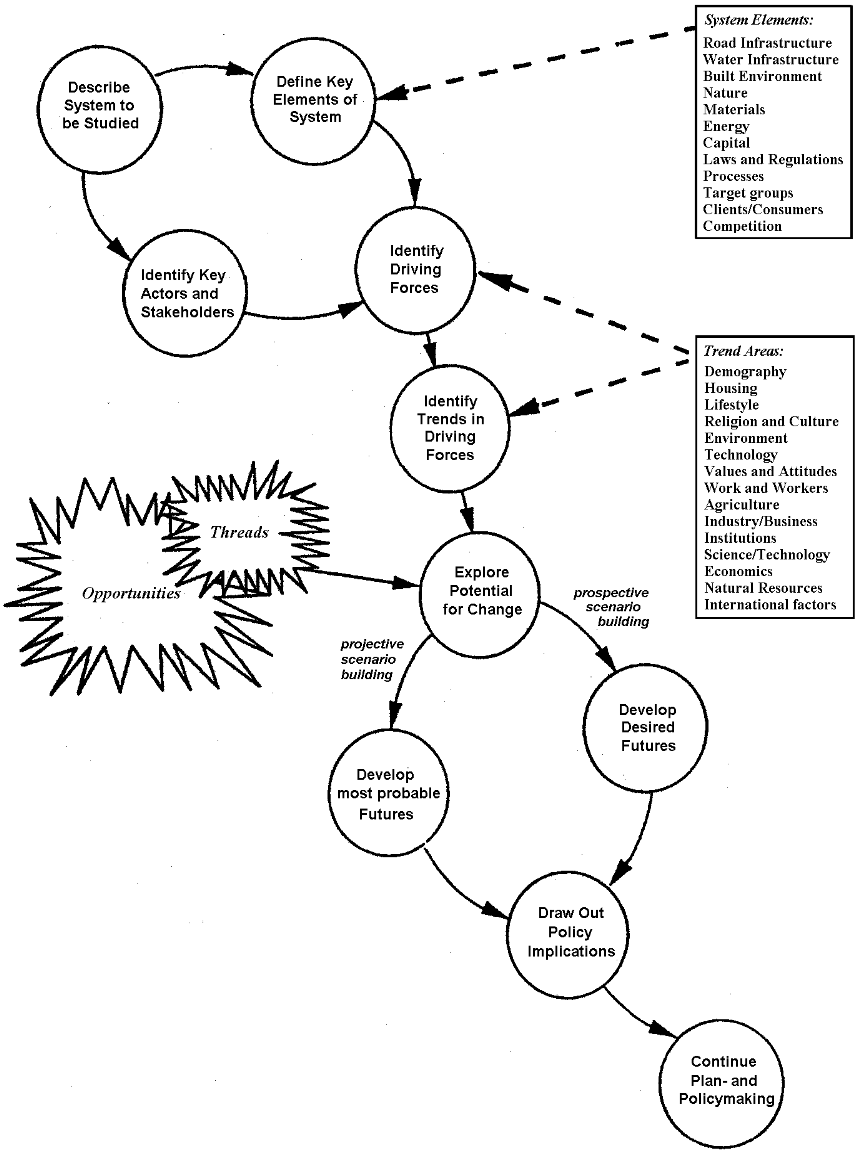
Figure 1. *Scenarios describe the present situation (I) and possible future situations (III) and a plausible route between both (II)*

Scenarios are written as *long-term* predictions of the future. A proper scenario involves a description of a future situation (III in Figure 1) and the course of events (II) that enables a system to move forward from the original situation (I) to the future situation (III). Scenarios often consider events such as new technology, population shifts, changing economic situations, for example, regarding consumer preferences, and different levels of government involvement, for example through investments.

The primary purpose of a scenario is to provoke thinking of policymakers who can then posture themselves for the fulfilment of the scenario(s). A most likely scenario is usually written, along with at least one optimistic and one pessimistic scenario, but of course other assumptions can also be used as leading motive.

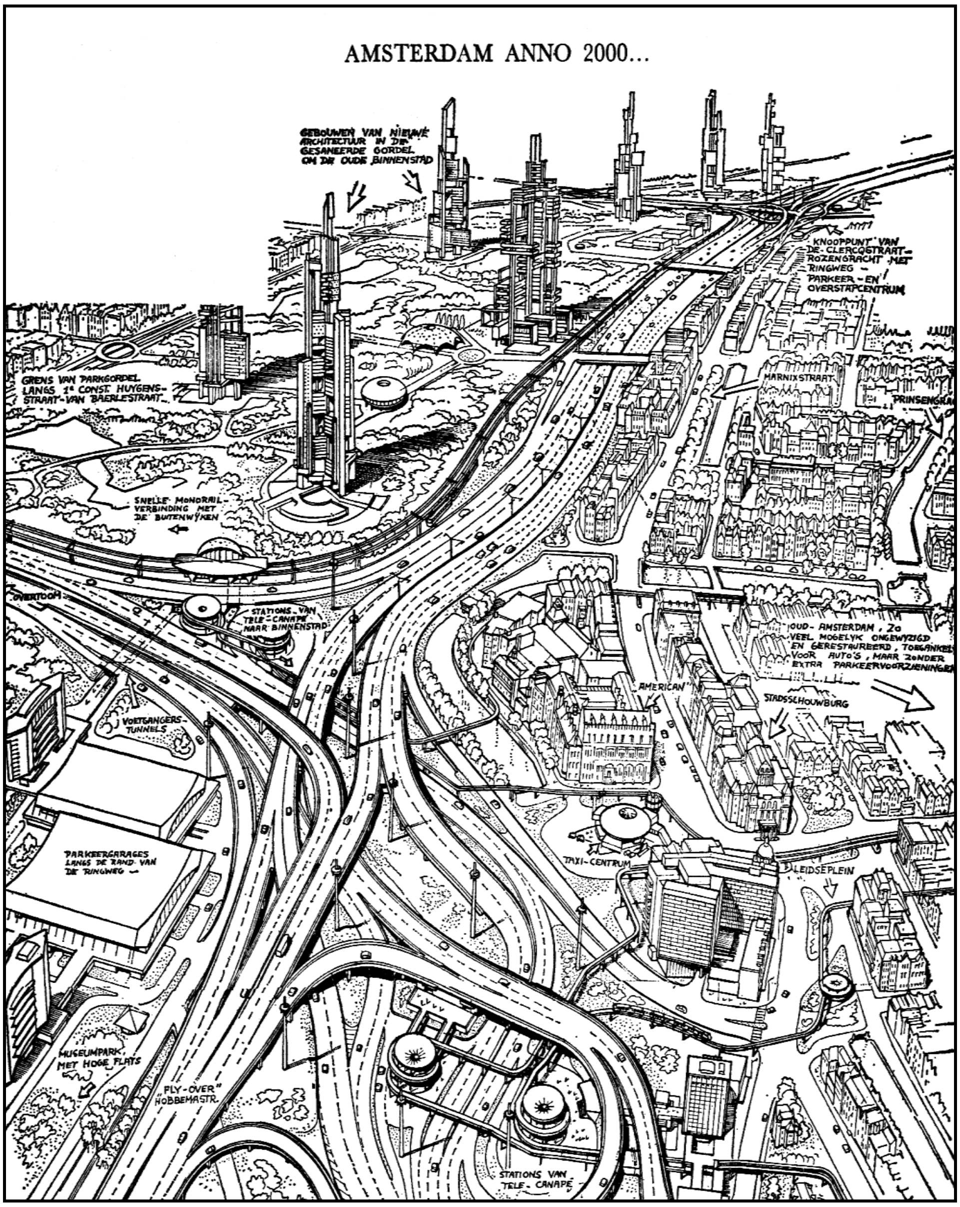
Two major types of scenario are often identified:

- *Projective scenarios* (sometimes also called exploratory scenarios): starting from past and present trends and leading to a likely future;
- *Prospective scenarios* (or anticipatory or normative scenarios): built on the basis of different visions of the future that may be desired or, on the contrary, feared.



(adapted from Coates, 1996)

Figure 2. *Example of an integrated scenario-working scheme*



Source: Das et al (1966)

Figure 3. *A 1966 view on the future of Amsterdam in 2000*

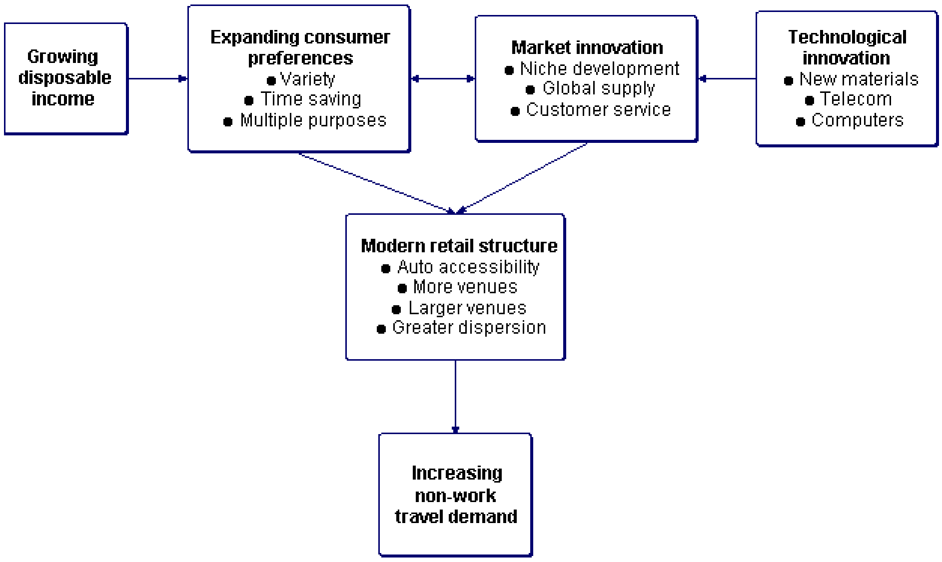
The preparation of a prospective scenario is also known as *backcasting* (Dreborg, 1996). It involves working backward from a particular desirable future endpoint to determine the physical feasibility of that future and what policy measures would be required to reach it (see for examples: Hojer, 1998). In Figure 2 an integrated working scheme is outlined that includes both a prospective and projective approach. This scheme is robust, i.e. it can be combined both with a Delphi-approach and with quantitative forecasting.

Visions of the future are of course very speculative, but very interesting for the exploration of new avenues of thought. See for example Figure 3, which is borrowed from a 1966 book on urban planning (Das et al., 1966). It shows a number of developments that are still 'futuristic' today, after 2000. For instance, the public resistance against demolition of houses for new developments has clearly been underestimated.

2.3 An example: Transit-Oriented Development

The Scenario approach can combine very well with the Delphi method. An example, borrowed from Nelson and Niles (2000), will be briefly summarized here. It concerns a study of a transit-oriented development (TOD). This is a mix of shopping, service, and recreational activities at urban centres linked together by a high quality transit system that induces citizens to drive less and to walk and use the transit system more often. Transit-Oriented Development (TOD) has rapidly emerged as the central urban planning paradigm in the United States. Leaders in many metropolitan areas have made, or are contemplating making, major investments in new rail transit capacity under the assumption that synergy between compact, mixed-use development and mass transit will change car-dependent growth and travel patterns.

The success of the TOD concept (Figure 4) depends greatly on the response of developers, consumers, and other economic actors to the new land use-transportation configuration. This has been a reason for applying a combined Delphi-Scenario method to learn more about potential effects. A multidisciplinary panel was created that included urban planners, architects, urban geographers, urban economists, commercial developers, store site selection managers, transportation planners, and environmental organization representatives.



(Source: Nelson and Niles, 2000)

Figure 4. *Theoretical Framework TOD*

Before undertaking the assessment exercise, they had to specify the problem and establish the purposes, goals, objectives, boundaries, and other important components of the TOD scenario exercise. Table 1 briefly describes some specific steps in the process.

According to Nelson and Niles (2000), the approach of Table 1 provides several advantages over other methods. It allows the setting up of a planning horizon that reflects the uncertainty inherent in these forces. In the ideal case, it would precede decisions to invest in transit capacity and would permit the involvement of a broader range of expertise than is normally the case in transportation and land-use planning. For example, retail industry site selection managers would share equal status with regional transportation planners. Most, if not all, of the significant forces shaping urban form would be considered. The land use-transportation scenarios evaluated would not be limited to the regional planning vision and to no-build or build transportation alternatives. Through the iterative process, other perspectives would be considered until a consensus is reached on a feasible scenario that is compatible with the forces shaping the urban environment.

Step	Scope
Describe present retail structure/patterns	Present urban structure including retail market, travel patterns, past trends
Identify forces shaping urban form	Understanding and subjective weighting of forces: economic, environmental, social, and technological. Focus on current and future market trends: commercial development, consumer behaviour, non-work travel patterns
Specify TOD scenario	Likely station-area locations and types (residential, retail, employment, mixed)
Specify transit system	Size and quality of transit afforded under fiscal constraints
Define success	Economic, societal, personal, and environmental benefits and costs; elaborate 16 planning factors; establish planning horizon
Evaluate success	Identification of constraints and supporting policies to achieve feasibility; adaptation to new knowledge and consideration of alternative solutions as needed

(Source: Nelson and Niles, 2000)

Table 1. *Stages in Delphi-scenario approach for TOD*

With a multi-disciplinary Delphi panel, broader social equity questions would also likely be considered, as well as a range of opportunity costs. The process can be open to the public in ways that quantitative forecasting cannot be. The empirical data, estimates, and assumptions would be available for public inspection. A report might be issued after each step, which would allow stakeholders, including elected officials, the opportunity to provide feedback throughout the effort. Information considered and techniques used would be transferable across regions.

3 Quantitative forecasting

Quantitative forecasting methods use numerical empirical data to forecast the future. The objective of these methods is to study past events in order to understand the underlying structure of the data and use that knowledge to predict future occurrences. Quantitative methods can be used in planning when one or more of the following conditions occur:

- A sufficient and consistent set of historical data on the variables to be forecast
- The likely stability of the relevant environment during the forecast horizon
- The forecast has a short time horizon, that is, five years or less.

The two most popular quantitative approaches will be briefly discussed here: 'Time series' forecasting, which involves projecting future values of a variable based on past and current observations of the variable (Pourahmadi, 2001; Chatfield, 1996; Weigend and Gershenfeld, 1994; Box and Jenkins, 1970) and 'Causal' forecasting, which involves finding factors that relate to the variable being predicted and using those factors to predict future values of the variable (Makridakis et al., 1998; Morrison, 1991; Wyatt, 1989; Anas, 1987; Wesolowsky, 1976).

3.1 Time series methods

A times series refers to data which is ordered according to the time of collection, usually spaced at equal intervals such as years. A planner is sometimes involved in a process whereby a forecast is needed for a variable with an unknown theoretical relationship to other predicting variables, for example, due to a lack of data. For instance, times series methods may be appropriate for forecasting in such cases as price developments over time in some sectors of real estate. Three specific time series methods are:

- Moving average
- Exponential smoothing
- Least squares trend analysis

The 'moving average' method is one of the simplest methods of forecasting. It assumes that a future value will equal an average of past values. The moving average method uses an average of a number of prior periods to forecast the next period. If a 2-period moving average is calculated, the average for the two prior periods is used as the forecast for the third period.

'Exponential smoothing' is a technique for averaging current and past observations in a time series. The procedure is based on a period-by-period adjustment of the latest smoothed average. Single exponential smoothing models require three items of data:

- The most recent forecast
- The most recent actual value
- A smoothing constant

The smoothing constant or 'damping factor' (w) determines the weights given to the most recent past observations and, therefore, controls the rate of smoothing or averaging. The constant's value must be between zero and one. The equation for the exponential smoothing model is:

(1) $F_t = wA_{t-1} + (1 - w)F_{t-1}$

Where: F_t = exponentially smoothed forecast for period 't'
A_{t-1} = actual value in prior period
F_{t-1} = exponentially smoothed forecast for prior period
w = smoothing constant or weight

To begin using the exponential smoothing method, the first actual value is usually chosen as the forecast value for the second period. The lower the smoothing factor is, the higher the importance attached to the most recent data (see Figure 5).

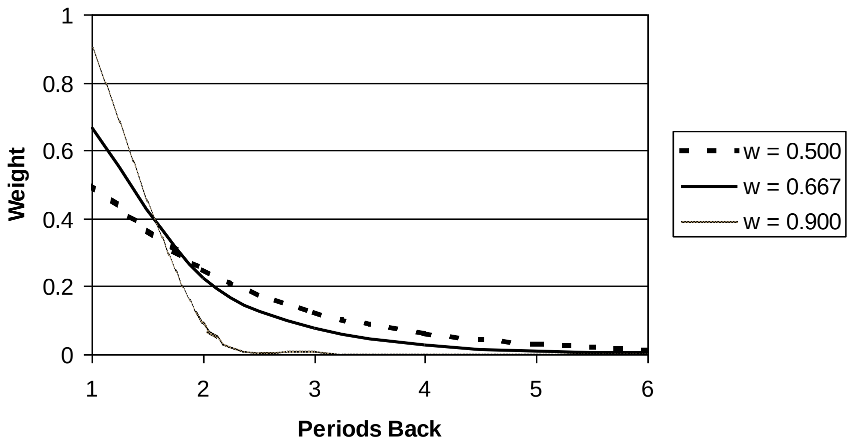


Figure 5. *Influence of smoothing factor*

The *least squares method* can also be used to determine the trend line. The method involves fitting a linear trend line through time-series data to obtain an equation for a line of the form:

(2) $Y_t = b_0 + b_1X_t$

Where: Y_t = forecast value for time t
X_t = year
b_0 = intercept of the trend line with the vertical axis, and

b_1 = slope of the trend line

The least squares technique means that the line is fitted so that the squared deviations between the predicted (forecasted) values and the actual values are minimized. Regression analysis is used to determine the trend line, whereby the years are the independent variable.

By using the least squares method also other functions than a straight line can be fitted to the data. Options include logarithmic, polynomial, power, and exponential functions.

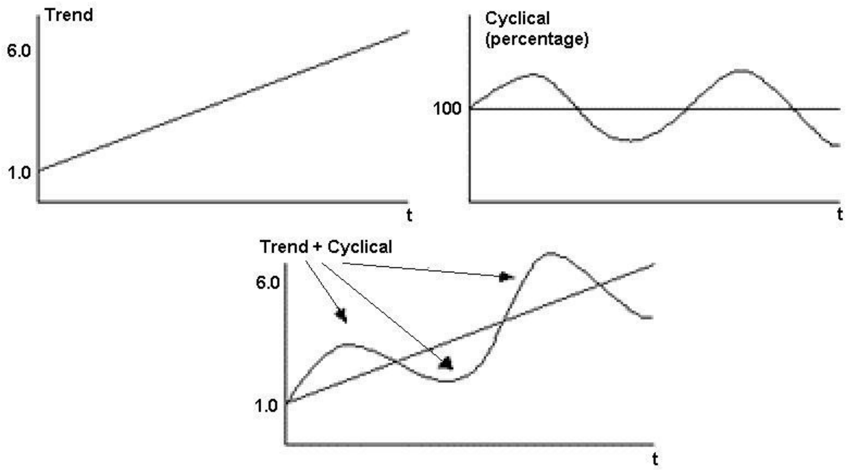


Figure 6. *Decomposition of a data pattern*

A forecast can be improved if the underlying factors of a data pattern can be identified and forecasted separately (e.g. see Figure 6). Breaking down the data into its component parts is called decomposition. For example, it can be assumed that housing sales are affected by four factors: the general trend in the data, general economic cycles, seasonality, and irregular or random occurrences. Considering each of these components separately and then combining them together makes the forecast.

A well-known forecasting method is *ARIMA* (Autoregressive Integrated Moving Average), also known as the Box-Jenkins approach. This method uses auto regression, differencing, and moving averages to estimate time series variables. Auto regression is the relationship of each value in a series to previous values. Differencing looks at the changes from one observation to the next and is used to stabilize a time series that seems to vary erratically. In a moving average process each value is determined by the average value of the current disturbance and one or more previous disturbances; a disturbance affects the value of the dependant variable for a finite number of periods and then abruptly ceases to affect it. Specialized computer software is necessary to use the ARIMA forecasting method and it requires a large amount of data, which is seldom available in spatial planning settings.

3.2 Causal forecasting

Causal methods search for factors that relate to the variable being predicted. Those factors are then used to predict future values of the variable. Causal methods include:

- Multiple regression analysis
- Econometric models
- Simulation models.

Multiple regression analysis is often used to learn more about the relationship between several independent or predictor variables and a dependent variable. The general computational problem that needs to be solved in multiple regression analysis is to fit a straight line to a number of points. A line in a two dimensional or two-variable space is defined by the equation

(3) $Y=a+b*X$

or in words, the *Y* variable can be expressed in terms of a constant (*a*) and a slope (*b*) times the *X* variable. The constant is also called the *intercept* and the slope is known as the *regression coefficient*. In the multivariate case, when there is more than one independent variable, the regression line cannot be visualized in the two-dimensional space, but can be computed just as easily. Multiple regression procedures will estimate a linear equation of the form:

(4) $Y = a + b_1*X_1 + b_2*X_2 + ... + b_p*X_p$

In equation (4) the regression coefficients (or *B* coefficients) represent the *independent* contributions of each independent variable to the prediction of the dependent variable. Another way to express this fact is to say that, for example, variable X_1 is correlated with the *Y* variable, after controlling for all other independent variables. This type of correlation is also known as a *partial correlation*.

The following example may clarify this issue. One would probably find a significant negative correlation between Internet use and household income, that is, it is probable that low-income families use the

Internet more frequently. At first this may seem odd; however, if we were to add the variable 'level of urbanization' into the multiple regression equation, this correlation would probably disappear. This is because in cities, on average, people have better Internet infrastructure and facilities, for example, access to broadband cable and ADSL, but low-income families also tend to be concentrated in cities. Thus, after we remove this geographical difference by entering the urbanization level into the equation, the relationship between household income and Internet use disappears because household income does *not* make any unique contribution to the prediction of Internet use, above and beyond what it shares in the prediction with variable urbanization level. Put another way, after controlling for the variable urbanization level, the partial correlation between income and use of the Internet is zero.

The regression line expresses the best prediction of the dependent variable (Y), given the independent variables (X). However, reality is rarely (if ever) perfectly predictable, and usually there is substantial variation of the observed points around the fitted regression line. The deviation of a particular point from the regression line (its predicted value) is called the *residual* value. The smaller the variability of the residual values around the regression line relative to the overall variability, the better is our prediction. If there is no relationship between the X and Y variables, then the ratio of the residual variability of the Y variable to the original variance is equal to 1.0. However, if X and Y are perfectly related then there is no residual variance and the ratio of variance would be 0.0. Usually the ratio falls somewhere between these extremes, that is, between 0.0 and 1.0. 1.0 minus this ratio is referred to as *R-square* or the *coefficient of determination*. This value is immediately interpretable in the following manner. If we have an *R-square* of 0.4 then we know that the variability of the Y values around the regression line is 1-0.4 times the original variance; in other words we have explained 40% of the original variability, and are left with 60% residual variability. Ideally, we would like to explain most if not all of the original variability. The *R-square* value is an indicator of how well the model fits the data (e.g., an *R-square* close to 1.0 indicates that we have accounted for almost all of the variability with the variables specified in the model).

Usually, the degree to which two or more predictors (independent or X variables) are related to the dependent (Y) variable is expressed in the correlation coefficient R, which is the square root of *R-square*. In multiple regression, R can assume values between 0 and 1. To interpret the direction of the relationship between variables, one looks at the signs (plus or minus) of the regression or B coefficients. If a B coefficient is positive, then the relationship of this variable with the dependent variable is positive; if the *B* coefficient is negative then the relationship is negative (e.g., the lower the income the higher the use of public transport). Of course, if the *B* coefficient is equal to 0 then there is no relationship between the variables.

Econometric models can be much more complex than a single multiple regression equation. They are often made up of a hundred or possibly many more equations, comparable to Equations 3 and 4. The basic characteristic of proper econometric models is that the calibration of the parameters and the reliability of the equations are empirically tested with statistical measures. However, the aggregate prediction outcomes of these models depend heavily on the quality of the data used and the errors that are generated by the structure of the model itself. For example, suppose variables A and B both have a value of 5 and an error of +/- 1; the aggregate value of A and B is C. If C = A + B we have an aggregate value between 4 + 4 = 8 and 6 + 6 = 12. In other words, the aggregate value C has twice as much error than the original variables. The amount of error considerably increases if a multiplicative relationship is assumed, namely C = A·B. Now the aggregative value varies between 16 and 36. In other words, C now has an error 10 times that of the original variables! Clearly, this illustrates that the more complex a mathematical model is, the more unreliable its outcomes are.
The same conclusion applies to 'simulation models'. Forester has been an important promoter of these models (Forester, 1961, 1971), which focus on a formal representation of processes. The main difference they have with econometric models is that the coefficients of a simulation model have a physical significance and are measured directly or determined by trial and error, that is, they are not deduced statistically. Hence, the 'plausibility' of the outcome is an important criterion for judging the usefulness of a simulation model.

3.3 An example: forecasting demand for sand

Causal forecasting will be illustrated by summarizing the Dutch history of forecasting the future use of aggregates. The production of building materials such as gravel, sand and clay usually involves the removal of considerable amounts of the land surface, often near rivers. In addition, in Europe materials such as hard rock and limestone are extracted from pits. However, local policymakers and the surrounding population usually do not appreciate this kind of 'destructive' land use. It is a clear example of a 'not-in-my-backyard' activity. For this reason, in several European countries the forecasting of demand is used to show opponents of mining that the building materials really are needed. The policymakers concerned use the forecasts to legitimise the provision of mineral permits, that is, the amount of land that is permitted for mineral extraction depends on the forecasted future demand for that particular building material. A multiple regression analysis is used as a forecasting technique both in the Netherlands and other European countries (Lehoc, 1979; Bundesamt für Bauwesen und Raumordnung, 1998; EIB, 2002; Department of the Environment, 1994).

This will be illustrated below with a chronological overview of the way regression models for concrete and masonry sand have been made in the Netherlands. Through the presentation of these models, the use of regression analysis will be explained (Ike, 2000).

Concrete and masonry sand, i.e. coarse sand, is considered to be a scarce building material in the Netherlands. This is not because of limited geological availability, but instead to limited 'land use planning' availability. The annual demand varies between 18.5 and 24.5 million tons per year. There has always been a problem accommodating this demand with sufficient supply. Since 1975, models have been developed for the prediction of industrial sand use ($V_{\mathbf{i}}$) where 'i' stands for 'industrial'. Industrial sand is the generic name for concrete and masonry sand, sand from limestone, silica sand and asphaltic sand. At that time, there were no separate consumption figures available for concrete and masonry sand. Consequently, the practical value of these models was limited due to inadequate insight into the demand figures of various sorts of sand. The consumption of concrete and masonry sand was determined by a factor of 0.83 of the future use of industrial sand. The real factor value was actually between 0.79 and 0.86. The uncertainties, however, were not taken into account. Because of the fluctuations in the consumption of different sands this approach is not recommended. From 1979 onwards, time series for industrial sand have also been developed.
One of the first models for industrial sand consumption was done by the Netherlands Economic Institute (NEI, 1976a, p. 13). The NEI linked the annual mutations in industrial sand consumption [$d(V_{\mathbf{i}})$] to the annual mutations of the total building investments [$d(BI_{\mathbf{tnr}})$] collected by the Central Bureau of Statistics (CBS), (see Equation 3.1). When doing these equations, one has to ensure that the explanatory variable, in this case the time series of building investments, is converted into present values.

(3.1) $d(V_i) = 0.769 * d(BI_{tnr}) + 0.376$ $\quad R^2 = 0.846 \quad R = 0.92$

standard error:	(0.116)	(0.126)	period of estimation
t-stat:	(6.62)	(2.98)	1966-1974

From a statistical point of view this is a good model. As a rule of thumb it is usually assumed that the correlation coefficient should be higher than 0.8 (Wesolowsky, 1976).
In this case R = 0.92, which is good. Another rule of thumb is that the t-values of the regression coefficients should be higher than 2 (in this case 6.62 and 2.98, respectively). A disadvantage of Model 3.1 is that it cannot directly forecast the consumption of concrete and masonry sand, only that of industrial sand.

In 1984, an Interdepartmental Commission for Aggregates (ICO working group) developed a new model based on a longer period of estimation. Also at this time a relationship was established between industrial sand consumption (V_i) and total building investments (BI_{tnr}) (see Equation 3.2). However, in this model no mutations were used except for annual figures (ICO, 1984, p. 26).

(3.2) $V_i = 1.619 * BI_{tnr} - 5256.6$ $\quad R^2 = 0.45 \quad R = 0.67$

t.stat	(3.24)	(- 0.65)	Period of estimation 1966-1981

The t-value of the constant factor of this model was too low. Also, the correlation coefficient did not exceed 0.67. In addition, Model 3.2 had to be corrected for autocorrelation (Ike and Voogd, 1984b, p. 19).
The ICO working group also produced a second model based on investments in housing (BI_{wnr}):

(3.3) $V_i = 2.392 * BI_{wnr} + 4724.3$ $\quad R^2 = 0.67 \quad R = 0.82$

t.stat	(5.4)	(1.6)	Period of estimation 1966-1981

Model 3.3 was soon rejected because it only dealt with one component of the building industry, namely housing. Commercial and industrial building as well as infrastructure building were not included in the model. As a result the model was seen as inadequate as developments in these sectors of the building industry can be quite distinct from those in the housing industry with different – even opposite – investment patterns.

In 1990 the Ministry of Housing, Spatial Planning and the Environment (VROM) presented a new model. In this model a relation was created between industrial sand consumption (V_i) and building production (BP_{vrom}):

(3.4) $V_i = 0.356 * \{0.748 * BP_{vrom(t)} + 0.152 * BP_{vrom(t+1)}\}$ $R^2 = 0.70$

			Period of estimation
std.error:	(0.005)	(0.264)	1971-1987

So, instead of *building investments*, the explanatory variable this time was the more comprehensive *building production*, based on figures collected by the Ministry. For instance, in 1997 the building production of the Netherlands was NLG 104.8 billion, while the building investments for the same year were determined at NLG 55.8 billion. Building investments can be considered a better explanatory variable than building production since production figures also include, for instance, deliveries between building contractors.

The VROM Model 3.4 for industrial sand was adapted in 1993. The building production (BP_{vrom}) was then rightly replaced by the total building investments (BI_{vrom}), which resulted in the following model:

(3.5) $V_{i(t)} = 0.69 * \exp\{-0.14*(TT)\} * \{0.62 * BI_{vrom(t)} + 0.38 * BI_{vrom(t+1)}\}$

std.error:	(0.01)	(0.04)	(0.35)
t-stat.:	(54.81)	(3.47)	(1.79)
2-tail sig.:	(0.00)	(0.00)	(0.09)

$R^2 = 0.706$; $R = 0.84$; Adjusted $R^2 = 0.701$; $DW = 1.45$; Period of estimation 1969-1987; $SE = 1918.4$

where:

$V_{i(t)}$ = Consumption of industrial sand in 1000 tons in year (t) according to the CBS

$BI_{vrom(t)}$ = Building investments in year (t) in NLG million, price level 1989, according to the ministry of VROM

$BI_{vrom(t+1)}$ = Building investments in year (t+1) in NLG million

TT = $(1971 - t)$ if $t < 1971$

TT = 0 if $t > 1970$, i.e. the component $\exp\{0\}$ is set to 1

However, the coefficients of $BI_{vrom(t)}$ and $BI_{vrom(t+1)}$ in Model 3.5 were only statistically significant for 91%. Often a level of significance of 95%

or more is required. This would imply a reduction of the model to one explanatory variable ($BI_{\mathbf{vrom(t)}}$).

Models such as 3.5 are not very robust. This can be illustrated by reducing the period of estimation by one year to 1969-1986. In this scenario the significance of Model 3.5 drops to 78%. This is partially caused by inaccuracies in the data and the fact that the model is 'fitted' by means of trend components (TT). In general it holds that the more coefficients that are included in a model, the higher the chance that one or more coefficients become insignificant.

In practice a disadvantage of both Models 3.4 and 3.5 is that is not easy to grasp how the model functions at first sight. Adapting and processing variables outside the model into new meaningful variables might improve this, provided, of course, that this can be theoretically justified. Transparent models will help to increase the support for decisions that should be based upon them.

After the creation of separate time series after 1979 for concrete and masonry sand, regression models became available. In 1995, Ike developed a consumption model for this type of sand that attracted much attention in the professional world (Ike, 2000). In this model, the so-called Equivalent Final Consumption (EFC) of concrete and masonry sand was linked to the building investments of VROM. The notion 'equivalent' means that the primary and secondary substitutes were also included, converted into units of concrete and masonry sand. These substitutes are important for environmental reasons. The total amount of building material (sand plus substitutes) is directly related to building investments. The notion 'final' means that the model also includes the consumption of sand that is used in the concrete industry for all kinds of concrete products whether imported or exported.

(3.6) EFC = 0.0005337 * BIvrom

st.error: (0.000004735)
t-stat: (112.72)
2-tail sig: (0.0000)

R^2 = 0.869; R = 0.93; DW = 1.94; Period of estimation 1979-1993; S.E. = 0.695.

This model appeared to be very robust. The correlation (R = 0.93) was high and the t-value had an exceptionally high value of 112.72. When the time series was subdivided into two periods, two almost identical equations could be created (Ike, 2000). It was also investigated whether the various sectors of the building industry, i.e. housing, commercial and industrial building, and infrastructure, could be included separately in the model via multiple regression. For this reason an initial check was made to determine whether the explanatory variables have a high intercorrelation in the period of estimation. This was true for housing investments and commercial and industrial building investments. The intercorrelation was 0.90 and 0.88, respectively. The rule is that if the intercorrelation is high with respect to the overall correlation, one of the two variables may be excluded. However, if one sector of the building industry is excluded the model would have been incomplete and consequently less suitable for forecasting. It is better to aim for a model that is, from a theoretical perspective, as 'complete' as possible. Therefore, the next step was to aggregate the investments in housing and commercial and industrial buildings and then to try and create a model with two, instead of three, explanatory variables. Unfortunately, this did not result in a satisfactory model.

In the models discussed above no attention has been paid to dematerialisation. By *dematerialisation* is meant that the consumption of an aggregate, per unit of building production or building investment, decreases over time. However, it is a process, which is most likely to fit a product life cycle (Roozenburg and Eekels, 1991). According to this theory, in the first stage of a product life cycle, a new material will be used hesitantly. The popularity of the product will increase to the highest level of product saturation, at which point the popularity of the product and its use will decrease. Each building material has its own product life cycle. For example, bricks have been used for centuries, while cement-based concrete has only been used in the last hundred years. The introduction of materials that substitute for an original aggregate could be included in a forecasting model by expressing the 'changes' or 'profits' in terms of equivalents of the building material under consideration. However, a dematerialization in which less aggregate is used because of constructive innovations is less easy to include in a model.

In 2001, the Netherlands Bureau for Economic Policy Analysis (CPB) published a new model of the consumption of concrete and masonry sand (CPB, 2001):

(3.7) $\ln(EFV) = 1.25 * \ln(Bivrom) - 0.007 * t + 0.39\ AR(1)$
t-stat: (5.3) (-2.7) (1.5)

$R^2 = 0.67$; $R = 0.82$; $DW = 1.8$; Period of estimation 1979-1995.

Model 3.7 is based on a log-linear relationship. According to Mannaerts (1997) this type of model is more appropriate for incorporating the dematerialisation problem. However, the Durbin-Watson (DW) test showed series correlation between the residues. The t-value is less than 2 and the regression coefficient is not significant. Therefore, from a statistical point of view Model 3.7 has a problem. It is up to the decision-makers whether this model is acceptable.

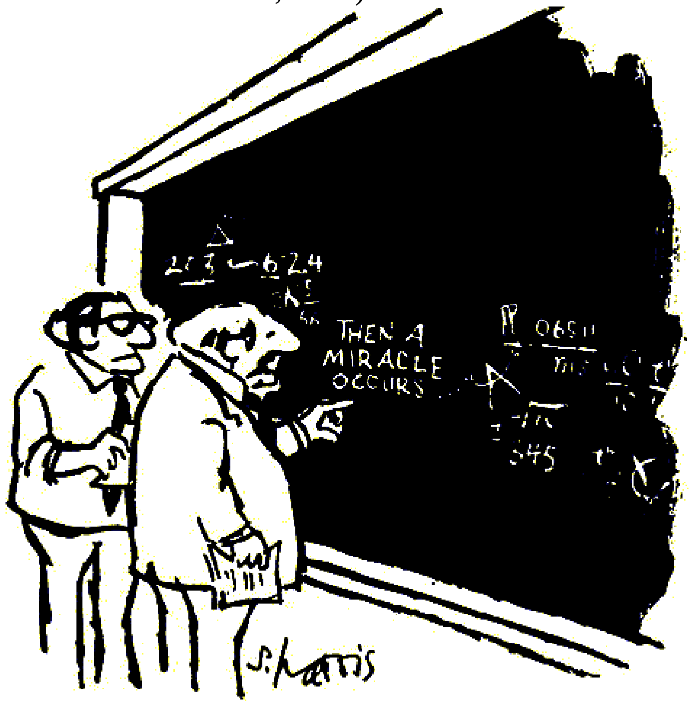
The conclusion from this overview is that in forecasting modelling all roads lead to Rome. It is clear that every author creates his or her own model. This seems to be a never-ending story. A practical recommendation from this could be to make models as simple as possible. The model-builder needs determination to exclude variables from the model that may seem interesting from a theoretical or political point of view. However, by increasing the number of variables the statistical significance is often reduced to an unacceptable level. In fact, the influence of variables that are left out of the model should be investigated in another way. For concrete and masonry sand, for instance, such variables could be the future use of alternative materials and dematerialization. These issues can be considered separately and discussed by all parties concerned.

4 Discussion

The famous philosopher Karl Popper argued in his book *The Poverty of Historicism* (1957) that it is not possible to predict the course of human history using scientific or any other rational methods, because such a prediction may influence the predicted event and hence distort the original forecast. This argument more or less explains why, in practice, reality often 'fails' to perform according to the forecasts made in earlier planning. Nevertheless, this does not imply that for this reason forecasting is a useless aspect of planning activity.

The academic interest in quantitative forecasting increased after the introduction of computers in the 1960s. Based on the new, seemingly unlimited, possibilities of these computers, detailed 'integrated disaggregated' quantitative models were developed. The general idea at that time was that if small models can predict well, it is reasonable to expect that bigger and more sophisticated models would do even better (for example Wilson, 1974). However, as outlined in Section 3.2, bigger did not turn out to be better. Specifically in the area of weather forecasting, it soon became evident that no matter what the size and sophistication of the models used, forecasting accuracy decreased considerably when applied beyond two or three days. As Lorenz (1966) showed, sensitive dependence on initial conditions could exert critical influence on future weather patterns, such as those caused by the flapping wings of a butterfly. In complex weather models a butterfly in Brazil was able to create a storm in Europe. This came to be known as the famous ‘butterfly effect’. In the short term as well, weather forecasting could not improve much on the accuracy of the naive approach, which predicts that the weather today or tomorrow will be exactly the same as today.

In other fields, similar experiences occurred and several authors concluded that large and sophisticated mathematical models were no more accurate than single equation models (Armstrong, 1978; Makridakis and Hibon, 1979).



"I think you should be more explicit here in step two."

Source: Harris (1992)

Evidently, forecasts can be very precise but quite inaccurate (Gordon, 1992). The limitations of predictability must be accepted in spatial planning as has already been the case in the natural sciences, where chaos is considered as important as order (Lorenz, 1991). It may be impossible to forecast the exact future of a chaotic system, but not impossible to anticipate its stability or instability. The uncertainty surrounding all types of forecasting should be acknowledged, and we should not expect to be able to forecast spatial-environmental systems any better than meteorological systems. Just as chaotic aspects govern the weather, so too do they affect spatial systems.

Last but not least, the influence of the forecaster's contextual environment should be stressed. Already thirty years ago convincing evidence was presented that local officials use biased (travel) demand forecasts to justify decisions based on considerations that are systematically too optimistic for reasons that cannot be explained solely by the inherent difficulty of predicting the future. Brinkman (2004) provides some empirical evidence that unethical behaviour and misuse can be invited by the political setting of the work. A quote in his paper from a modelling expert explains it all: *"I knew what my board wanted and I had the model over there telling me, 'Hey, I can't give you the numbers that are going to be that good.' Well, I've had to close the door of my office and go in and totally fabricate numbers."*(Brinkman, 2004, 256).

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