DYNAMIC BAYESIAN BELIEF NETWORK FOR THE DEVELOPMENT OF WALKING AND CYCLING SCHEMES

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ABSTRACT

This paper aims to describe a model which represents the formulation of decision making processes (over a number of years) affecting the step-changes of walking and cycling (WaC) schemes. These processes, can be seen as being driven by a number of causal factors, many of which are associated with the attitudes of a variety of actors, in terms of both determining whether any scheme will be implemented and, if it is implemented, the extent to which it is used. The outputs of the model are pathways as to how the future might unfold (in terms of a number of iterative time steps) with respect to specific pedestrian and cyclist schemes. The transitions of the decision making processes are formulated using a qualitative simulation method, which describes the step-changes of the WaC scheme development in an iterative and interactive manner. In the paper a dynamic Bayesian belief network theory is adopted in a way that each factor will collectively contribute to the transitions so that the influence between and within factors on the dynamic decision making process is taken into account.

Keywords: Bayesian belief network, causal effects, walking and cycling (WaC), dynamic decision making.

1. BACKGROUND

It is now generally recognized that the transport sector needs to play a key role in combating climate change and avoiding problems associated with limited supplies of fossil fuels. In such a context the advantages of walking and cycling modes are obvious as they contribute to sustainable transport goals, to build healthier and more sociable communities, and to contribute to traffic reduction. The amount of walking and cycling in Britain has declined over the long term. Between 1995/7 and 2006 the number of trips per person made by bicycle fell by around 20% and the average distance travelled by 9% (DfT 2007). The proportion of people cycling to work in Britain fell from 3.8% in 1981 to 3.0% in 2006 (DfT, 2007). In contrast, much higher levels of cycling are apparent in some parts of Northern Europe, with 28% of urban trips in the Netherlands made by bicycle (Pucher and Dijkstra, 2003), perhaps partly as a result of provision of high quality facilities and recent initiatives to promote policies such as bike and ride (Martens, 2006). Within Britain there is wide divergence in the use of cycling, with cities such as York, Cambridge and Oxford having much higher levels than the national average. As far as walking is concerned, the number of trips in Britain made by walking has decreased from 35% in 1975/76 to 24% in 2006 (DfT, 2007). By its very nature walking is something that virtually everyone does though households without a car walk on average 65% further than those with a car. Nearly 30 years ago Hillman and Whalley (1979) concluded that: “in both transport policy and practice, it [walking] has been overlooked or at the least, has been inadequately recognised”. This may in part have been due to a feeling that walking “will take care of itself” (Litman, 2003) and that walking is a benign mode of transport in the sense of having few adverse impacts. Pucher and Dijkstra (2000) report that transport and land use policies have made walking “less feasible, less convenient, and more dangerous”. Formidable obstacles to walking remain such as low density sprawl generating long trip distances, narrow or non-existent footways, inadequate crossing facilities and the growth of motorised traffic. It has been suggested that there are major obstacles to prevent people from using WaC modes in Britain. There have been many national and local initiatives to promote walking and cycling but without a long term vision and consistent strategy it is difficult to see how a significant change may be achieved. The time is now right to examine the means by which such a fundamental change both in the quantity of walking and cycling, and in the quality of the experience can be achieved, which goes well beyond continuation of existing trends.

From a planning point of view, there is a general interest from transport planning authorities in developing schemes to make these modes (i.e. WaC) more attractive. It is desirable to be able to make predictions of the long-term future impacts of such schemes and to use a model for making such predictions. Any such model needs to take into account a number of specific factors of importance to the pedestrian and cyclist modes. Firstly, it is typically the case that pedestrian and cyclist schemes are implemented by local authorities in an incremental piecemeal fashion, with successive elements of the scheme only being implemented once previous parts of the scheme have proven to be “successful”, in terms both of usage and overall public acceptability. It is therefore desirable for a model representing the step-changes of walking and cycling in response to such schemes to be dynamic in nature, representing a number of sequential stages. Secondly, since many causal factors affect, in complex interactive forms, both the attitudes of local authorities and (potential) pedestrians and cyclists, it is appropriate that such a model be based upon system dynamics principles incorporating causal chains and loops. Thirdly, if cycling and walking are to have significant impacts on climate change and transport energy usage, there needs to be a step change in the attitudes of trip makers who are currently using motorized modes if they are to switch to walking and cycling. Hence a system dynamics model representing pedestrians and cyclists should take into account that the behaviour of future (actual and potential) pedestrians and cyclists might be significantly different from the behavior that can be observed at the current time. The combination of these three factors presents significant challenges to modelling. To this end, this paper puts forwards a causal modelling technique which represents the formulation of decision making processes (over a number of years) affecting the step-changes of WaC schemes. These processes, can be seen as being driven by a number of causal factors, many of which are associated with the attitudes of a variety of factors, in terms of both determining whether any scheme will be implemented and, if it is implemented, the extent to which it is used. The outputs of the model are pathways as to how the future might unfold (in terms of a number of iterative time steps) with respect to specific pedestrian and cyclist schemes. The transitions of the decision making processes are formulated using a qualitative simulation method, which describes the step-changes of the WaC scheme development in an iterative and interactive manner. The details of the adopted modelling technique are described in the next sections. The main objectives of this paper are therefore twofold. On the one hand, we formulate causal mechanisms affecting the propensity to WaC under a variety of driving factors and the causal links between them. On the other hand, we propose a Dynamic Bayesian Belief Network to mathematically model the causal relationships between driving factors and the propensity to WaC over time in an iterative and interactive manner.

This paper is organized as follows. Section 2 describes a causes and effects model for the step-changes of the perception of people to a number of walking and cycling schemes. Then we illustrate the concept of Bayesian Belief Network (BBN) and how it is adopted to mathematically characterize the causes and effects model in Section 2. Section 4 presents a method to extend the BBN for a static causes and effects model to a so-called Dynamic Bayesian Belief Network (DBBN) for the dynamic nature of the step-changes of the perception of people over time. Finally, we conclude the paper Section 5 with a simple example to numerically describe the performance of the DBBN for modelling the step-changes of the walking and cycling schemes over time.

2. CAUSES AND EFFECTS MODELING

This section presents a model of the causal mechanisms affecting the propensity to walk and/or cycle within pre-defined user-groups of the population. The causal factors will in some cases be measurable, but in many cases will be qualitative. The causal factors are, of course, influenced by implemented transport, but the population is also influenced at any time t by future *plans* (if publicised), not just what has already been implemented by time step t ($t=0,1,2,\ldots$) with each time step in the order of 1-2 years. As well as the implemented schemes and plans up to and including (the start of) time step t, the inputs to the model include any other causal factors, including any exogenous 'drivers'. The primary output from the model is the propensity to walk/cycle in time step t (disaggregated by user group), given the assumed causal mechanisms. The motivation of the model is to represent WaC as something quite distinctive from other transport modes. There appear to be many distinctive elements of WaC, but two particular ones that motivate the model are:

- individuals' physical limitations, or at least their perceptions of these limitations, which (aside from those with mobility impairments) do not feature so prominently in the analysis of motorized modes; and

- the ‘collective reinforcement’ effect in terms of security, ‘safety in numbers’, a kind of “anti-congestion” in that the coincidence of collective actions make the activity more attractive (in contrast to traffic congestion).

We focus now on the group level demand model, shown in Figure 1. If we consider a randomly selected individual within a certain ‘user group’, it is proposed that altogether the propensity to WaC is directly conditioned by four main, multi-faceted factors:

- **Perceived Comfort-Zone:** A spatial representation of what an individual perceives to be their own personal physical limit of trips or trip segments that are possible by WaC.
- **Environment**: How attractive/conducive do individuals perceive the environment to be within which they could conduct WaC trips?
- **Availability**: How feasible is it to include WaC as part of an overall activity pattern?
- **Group Social Norms:** ‘Intrinsic’ values/beliefs, resulting from the era and location, and ‘Conditioned’ values, shaped by personal/others’ experiences/beliefs of the transport system.

The general thinking behind the Perceived Comfort-Zone definition is to group together those factors that pertain to an individual’s own perceived physical limitations as part of their normal weekly/daily activities. That is to say, it is not defined by the limits of human endurance, but is related to the perceived level of exertion that an individual is comfortable with expending as part of their normal activities.

The terms used in the four elements above are primarily meant to be *groupings* of causal factors, but on the other hand the groupings have been chosen with one eye on the mathematical mechanisms by which we might actually represent the propensity. Loosely speaking, we might think of the Comfort-Zone and Availability factors to define/restrict the travel choices available, and Environment and Group Social Norms to respectively define the individual-level and social group-level stimuli motivating the choice of travel option from those available. In this way, increasing the use of WaC is both about breaking down participation barriers to widen its perceived availability as an option, as well as about making the experience more pleasant for those who choose WaC.

In Figure 1, the causal factors underlying the four main conditioning elements of Group Social Norms, Perceived Comfort-Zone, Environment and Availability are proposed. The notation adopted is that a policy measure/lever is represented by italicised writing in a dashed box (and in blue for those looking in colour); a direct causal factor is represented by unitalicised text in an unbroken box; and the various reinforcement effects (to be defined) are represented in small capitals in a dashed box (and in brown for those looking in colour). Each of the four major elements described are now considered in turn below, before considering the reinforcement effects.

Perceived Comfort-Zone

As noted earlier, the idea behind the notion of a Perceived Comfort-Zone is to reflect how the perceived comfortable level of physical activity that an individual is prepared to expend as part of their normal daily activity is reflected in the spatial ‘network’ they perceive to be available to them to conduct WaC activities. This has several **causal factors**:

Distance separation of activities: Reflecting the fact that as residential and other activity locations become more separated, this will have a potentially negative consequence on WaC. Clearly an individual will have a range of typical activities to perform, so a range of distances, so some thought needs to be made on how to reflect this simply.

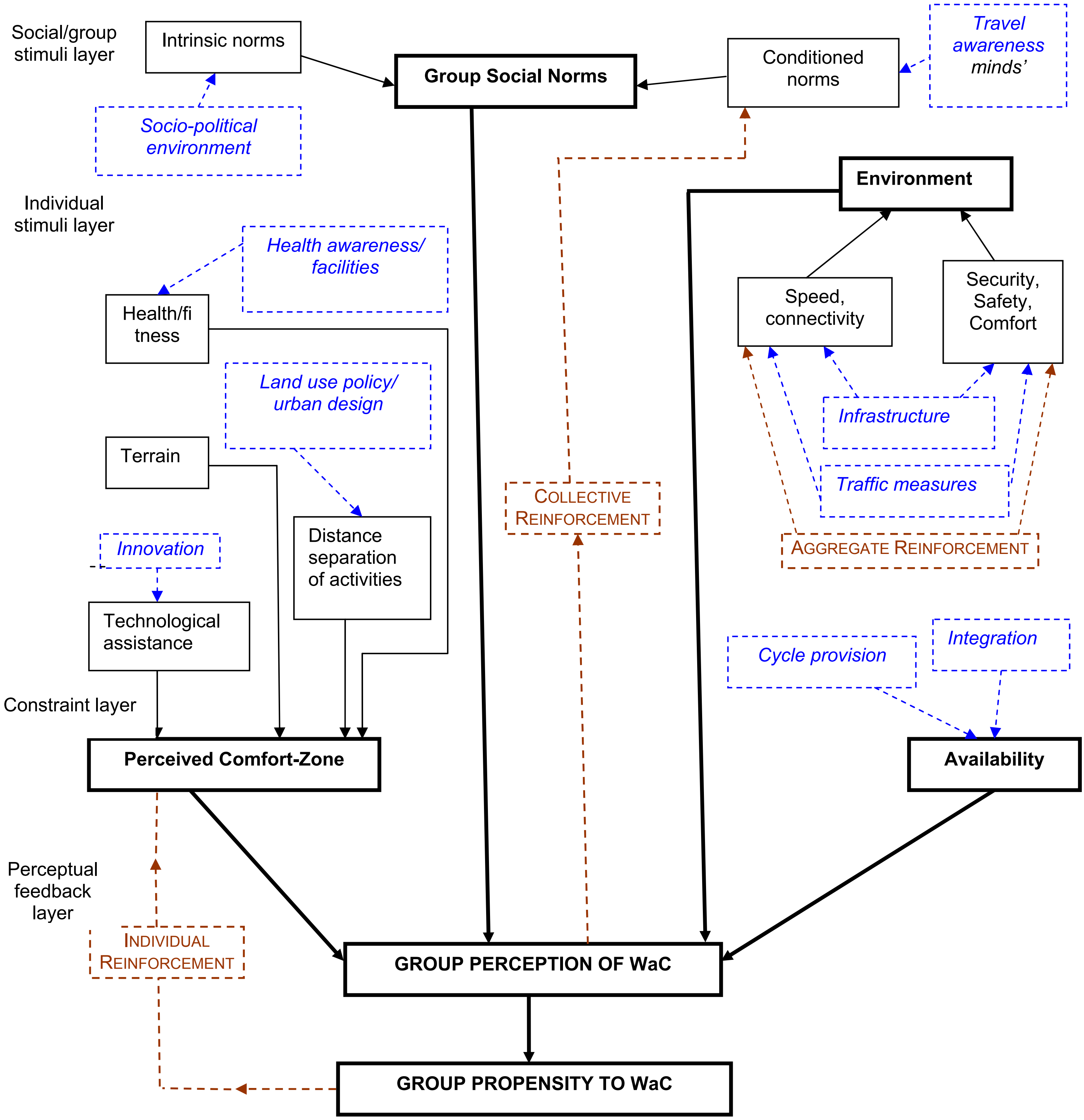

Figure 1- Conceptual demand-side model of propensity to WaC within a "group"

Terrain: Certainly for cycling, and for less able-bodied for walking too, the hilliness of the terrain has a major effect on the physical exertion. Generally we may not think we can affect this variable in any way, though since it is a measure of the terrain experienced by an individual as part of their normal trip pattern, there are potential indirect impacts from changes in residential location/land-use (though these are not reflected on Figure 1). This factor may be particularly useful in explaining issues of non-transferability between locations.

Technological assistance: There is a whole range of possibilities in this category, including currently available devices used for storing energy and/or genrating energy while cycling, to assist in climbing hills.

Energy limit: A reflection of both perceived and actual health/fitness levels of an individual, in terms of a measure of the personal physical 'energy' they believe they can comfortably expend as part of a WaC activity. Note that by defining the limit in energy as opposed to distance terms, we are able to make connections to overall health/mobility levels, and subsequently relate overall WaC 'availability' to the terrain faced and measures that affect the separation of activities.

Several **policy levers** also may have a potentially significant impact on the factors above:

Land use policy/urban design: As work, shopping, school and home activities have become more dispersed over recent decades, so the demands on travel have changed in terms of their pure separation. Thus future policies to encourage the provision of local shops, leisure facilities, jobs and schools have a potentially very positive impact on the possibilities to conduct shorter distance trips that are more amenable to WaC (eg walk to the local butcher rather than drive to out-of-town Tesco). A modern sense of 'local' might be local to place of work (eg provision of city centre health drop-in centres, provision of shopping at rail stations), not only local to home?

Health awareness/facilities: Promoting healthy lifestyles as well as providing local facilities (eg swimming pools) also has the potential effect of producing more active and fit individuals across all age groups, which positively impacts on the perceived ability levels to perform WaC.

Environment

The heading of 'Environment' is intended to reflect both the real and perceived attributes of the personal environment in which one engages in WaC. This has several factors:

Security, safety, comfort: In many urban areas there are both real and exaggerated fears of personal security while walking, that vary by sex and age, as well as fears of accidents between pedestrians/cyclists and motorised vehicles. On the issue of comfort, the provision of shelters, not only at stops but also perhaps along a street, might greatly change the attitude to walking comfort during wet and/or windy conditions. For cyclists, security also refers to the availability of good, lockable facilities for leaving bicycles at a destination.

Speed, connectivity: It is not only safety but also travel time that can be affected by the provision of appropriate facilities, whether pedestrian crossings or cycle-ways, particularly when interactions occur with motorized traffic. Perceived lack of connectivity of the network may be as a result of real or perceived barriers; for example, reserved cycle-ways may often stop just before major intersections or narrow busy roads, due to the difficulty/cost in fitting them in. Connectivity thus moves the focus towards such barriers, and away from (say) trip-km of network, as has been common in cycling policy.

There are many policy measures that may be brought to bear on these factors:
Infrastructure: Investing in the many measures that exist to improve both the security (cycle lanes, lighting, etc.) and connectivity of the network.
Traffic measures: This comprises both reallocation of road space for the existing demand by alternative modes, and in suppressing or diverting motorized traffic in a desirable way.

Availability

The third aspect related to WaC concerns real issues of availability of these modes as feasible travel alternatives (and ways in which this availability may be improved). Factors pertinent to this aspect include:

Cycle Provision: This includes both cycle ownership (and incentives for this), and the provision of cycle hire facilities, including ‘smart-card’ facilities. As part of this provision, cost will presumably also be a factor, whether purchase/maintenance or hire cost. If WaC is an element of a choice between, say, walk+public-transport versus car, then the relative costs of the other transport modes may also be pertinent.

Integration: concerns the potential for integrating WaC with the use of other modes. This includes proximity of bus/train services to residential and activity locations (‘within walking distance?’) and the accessibility of these services to the rest of the network. It may also include provisions for carrying cycles on trains, cycle lockers, and pedestrian interchange facilities.

Group Social Norms

Attitudes of friends, family and work colleagues play a major factor in the perceived environment, over and above an individual’s personal experiences. This includes both the positive potential for identifying WaC with environmental awareness, and in addressing real fears as well as dis-spelling myths about the perceived difficulties by non-WaC users.

It seems there are at least two distinct facets of such norms, which are reflected in Figure 1:

Intrinsic Norms are those unrelated to the transport system *per se*, but are more related to the generation, era and general political climate that individuals within a group are living. While we might consider the ‘socio-political environment’ as fixed for our transport system, there are potential ways for affecting change, such as a generally greater involvement of a group in the decision-making processes of a region or city (not just transport).

Conditioned Norms, on the other hand, are internal to the transport system, and something where careful attention is needed to produce positive images that will shape future decisions.

The main **policy lever** represented is thus:

Travel awareness: Communicating desirable outcomes to community groups, travel-plans, and public awareness campaigns about the negative energy/environmental impacts of dependence on motorised transport, and the positive experiences of walkers and cyclists, are all ways of shaping perceptions of the WaC environment.

Reinforcement effects

In several transport modes, there are well-known negative effects of greater usage, such as the effect of greater use of private transport on congestion or the greater use of public transport on in-vehicle comfort (at fixed service levels). As noted earlier, walking and cycling seem distinctive in that there are several potentially positive effects of greater usage, in terms of encouraging still further usage in the future, and in terms of building pathways to substantially increased usage, these effects seem especially important to capture and understand. They are referred to here as ‘reinforcement effects’ as they all act in a positive way to further enhance the actual and/or perceived attractiveness of WaC. So in contrast to some of the ‘negative spirals’ of cause and effect observed in other transport modes, we have the opportunity to stimulate a positive spiral.

Three main reinforcement effects are represented in Figure 1, using small caps font (and brown for those looking in colour), and these are as follows:

Aggregate Reinforcement: This may also be termed ‘safety in numbers’: the fact that in cities where there are large numbers of cyclists, so cycling feels (and is) safer, and similarly as it becomes more normal to walk so there are fewer deserted areas, and therefore fewer concerns about personal safety (and it really is safer too). It is suggested that this happens at the aggregate level across all groups: in terms of actual (rather than perceived) safety in numbers for cycling, it seems irrelevant which social group the riders belong to. In terms of walking, perhaps it is not merely aggregate number of pedestrians, in the sense that the mix of groups may also matter.

Individual Reinforcement: This reflects the fact that an individual, by engaging in WaC, (a) is likely to improve their own health/fitness, and therefore see WaC as a more viable option in the future, and (b) will get a direct psychological feedback on what they think their Perceived Comfort-Zone to be (actually, this may be positive or negative).

Collective Reinforcement: This intra-group effect reflects the potential feedback from increased use of WaC to Conditioned Norms within a group concerning the viability and desirability of WaC. The idea is that as WaC becomes more widespread then it has a potentially positive reinforcement in being seen as a more ‘normal’ or desirable activity within a social/peer group.

Therefore there are all kinds of potential benefits in individuals and groups receiving very positive early experiences of WaC. In thinking how this reinforcement may work, an analogy might be drawn here with models of ‘product innovation’, in which an S-shaped logistic relationship is typically observed. What this means is that when WaC is conducted by few people, there is no reinforcement effect, as they are too sparsely spread to significantly impact on feelings of safety, security and social norms. But as there is more take-up of the WaC ‘product’, so a positive reinforcement occurs that this engenders further take-up by its positive impact on the WaC environment. At some point it also makes sense that this reinforcement may reach a saturation limit too, so there is a level of engagement in WaC at which the positive reinforcement levels off.

A further analogy might be made with economic terminology: it seems that the aggregate reinforcement, which has impacts outside of a group, provides a potentially ‘positive externality’, and (assuming the expression exists!) that the two intra-group reinforcement effects provide a potential 'positive internality'.

3. DYNAMIC BAYESIAN BELIEF NETWORK THEORY FOR MODELING CAUSAL LOOP EFFECTS

This section describes a method to mathematically model the causes and effects between factors presented in Section 2 affecting the decision to implement a walking and cycling scheme over time.

Bayesian Belief Network

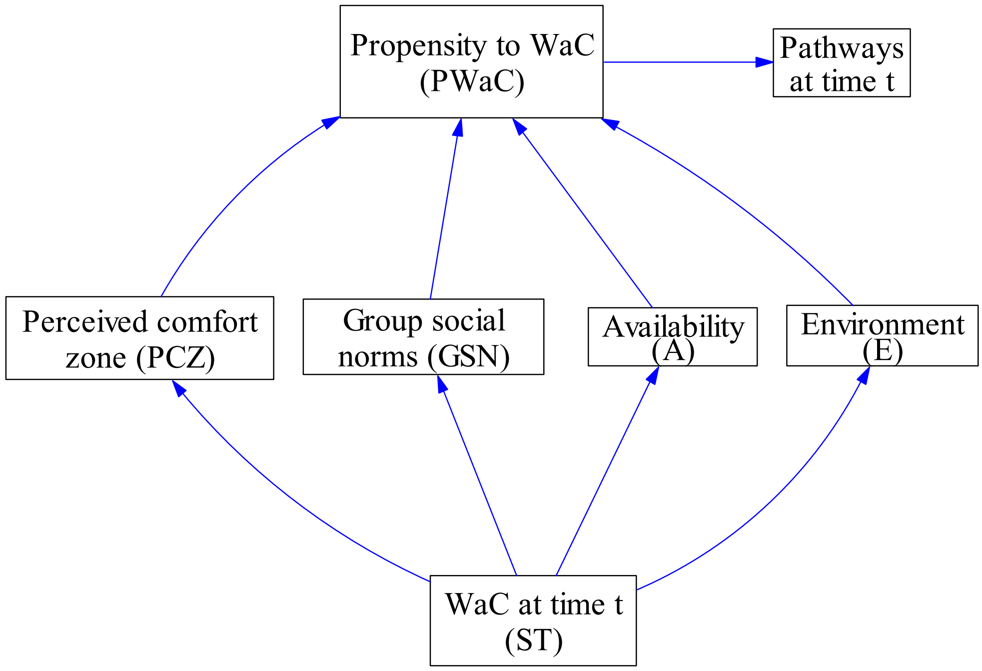

Figure 2 Causal loops to determine the Propensity to WaC from the four main factors.

The concept of a *Bayesian belief network* (BBN) has been found in many applications described in the literature (Jensen,1996, Neil et al.,1999). In principle, a BBN is a *directed acyclic graph* (DAG) which encodes the causal loops between particular factors represented in DAG as nodes. For example, Figure 2 describes the causal loops between the four main factors Perceived Comfort Zone (*PCZ*), Group Social Norms (*GSN*), Availability (*A*), Environment (*E*) and the Propensity to WaC (*PWaC*), given a WaC Scheme implemented at Time *t* (ST). Based on the *PWaC*, the *Pathways* (*PW*) at time t are constructed from the algorithm presented below. In Figure 2, we model *ST, PCZ, GSN, A, E, PWaC* and *PW* as nodes, whereas the arrowed links between those nodes are considered causal links. In addition, by definition the causal links connect *parent nodes* (causes) to *child nodes* (effects). So in Figure 2, *ST* is the parent of *PCZ, GSN, A* and *E*, while *PWaC* is the child of all four nodes *PCZ, GSN, A* and *E*. Before going into details about the BBN for modelling the causal loops, let us begin by giving some definitions and notation:

Z: state vector indicating the level of acceptance {high, medium, low}.

X: variable vector describing the state of the nodes in Figure 2. *X={x_n}*, where x_n is the variable depicting each node *n*.

P(X=Z): the probability of the variable X in a particular state in ***Z***. For example, *P(PCZ=high)* denotes the probability that a WaC scheme will exert a high influence on the Perceived comfort zone. The relationship between joint and conditional probability is obtained from probability theory as:

$$P(x_1, x_2, ..., x_N) = \prod_{n=1}^{N} P\left(x_n \mid Parents\left(x_n\right)\right) \tag{1}$$

The decomposition in equation (1) will provide a means for specifying the transitions of the decision process as in the context of a system dynamics which is detailed in the rest of this section. By breaking the transition probabilities into a product of conditional probabilities, we could better judge which of the factors we may assume as being invariant in time and which may be time-dependent. The main point is that the decomposition in equation (1) will focus the modellers' attention upon explicitly deciding which factors may be assumed time-homogeneous and which are not.

As specified in Figure 2, a node with more than one parent such as *PWaC* must require their conditional probability distribution to be provided in a form of conditional probability table which specifies the conditional probability of the child node being in a particular state (i.e. high or low), given the states of all its parents: $P(PWaC \mid PCZ, GSN, A, E)$. From equation (1), the conditional probability is a summarized form of the joint probability distribution. Hence:

$$P(PWaC) = P(PWaC \mid PCZ, GSN, A, E)P(PCZ)P(GSN)P(A)P(E) \tag{2}$$

Since *P(PCZ), P(GSN), P(A)* and *P(E)* are all dependent on the WaC scheme implemented at time *t*, a further break-down of causal relationships between PCZ, GSN, A and E with ST are constructed using information provided in Figure 1.

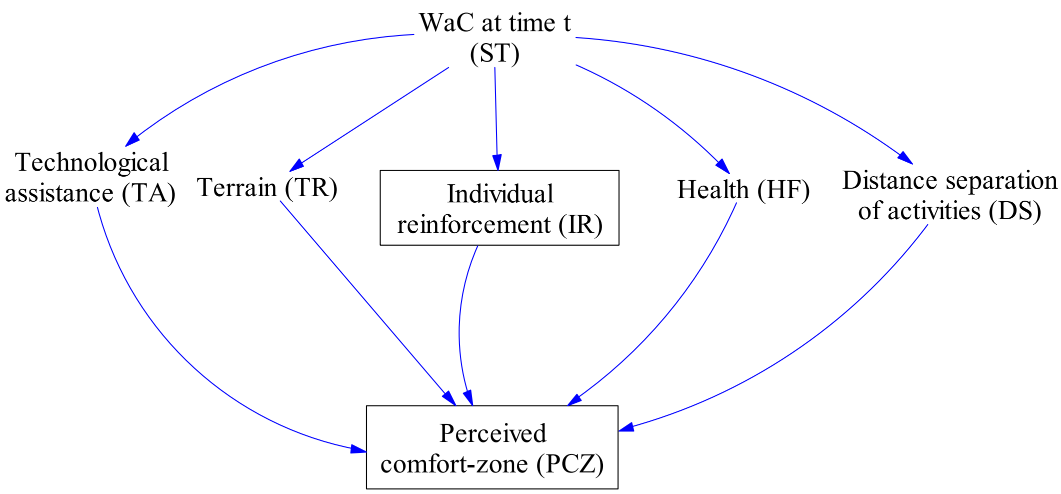

Figure 3 Causal loops to determine the *P(PCZ)* from the WaC scheme at time *t*

Figure 3 describes the directed acyclic graph (DAG) of the child node *PCZ* given the parent node *ST* at time *t*. From Figure 3, node *PCZ* is the child of many parents such as Technological Assistance (*TA*), Terrain (*TR*), Individual Reinforcement (*IR*), Health and Fitness (*HF*) and Distance Separation of activities (*DS*). Based on the DAG in Figure 3, we can compute *P(PCZ)* as:

$$P(PCZ) = P(PCZ \mid TA, TR, IR, HF, DS)P(TA)P(TR)P(IR)P(HF)P(DS), \tag{3}$$

where *P(TA), P(TR), P(IR), P(HF)* and *P(DS)* denote the probabilities that a given WaC scheme *ST* could influence Technological Assistance, Terrain, Individual Reinforcement, Health and Fitness and Distance Separation of activities, at a level of high, medium, or low.

Figure 4 describes the DAG of the child node *GSN* given the parent node *ST* at time *t*. Based on the DAG in Figure 4, we can compute *P(GSN)* as below:

$$P(GSN) = P(GSN \mid SE, CN) P(SE \mid IN) P(CN \mid CR) P(CR \mid TrA) P(IN) P(TrA), \qquad (4)$$

where:

- *SE*: Social political Environment.
- *CN*: Conditional Norms.
- *IN* : Intrinsic Norms.
- *CR* : Collective Reinforcement.
- *TrA* : Travel Awareness.
- *P(IN)* and *P(TrA)*: the probabilities that a given WaC scheme *ST* could directly influence intrinsic norms and travel awareness, respectively.
- *P(SE|IN)*: conditional probability that the social political environment is affected by intrinsic norms.
- *P(CN|CR)*: conditional probability that the conditioned norms is affected by collective reinforcement.
- *P(CR|TrA)*: conditional probability that the collective reinforcement is affected by travel awareness.

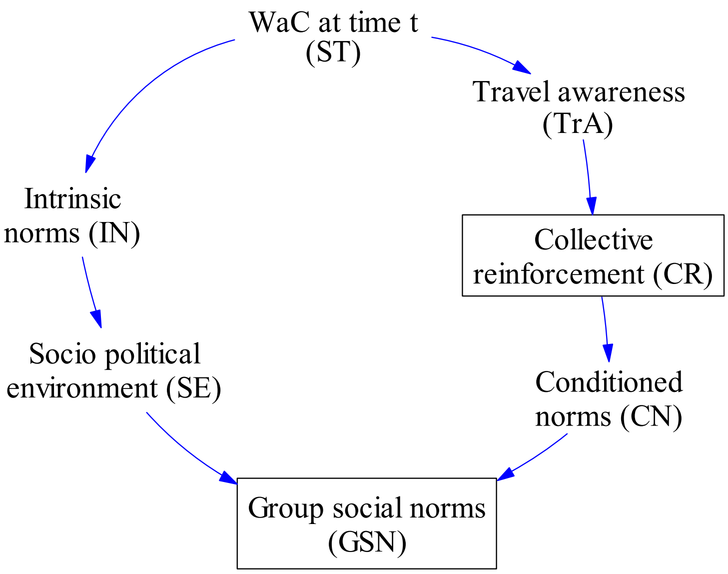

Figure 4 Causal loops to determine the *P(GSN)* from the WaC scheme at time *t*

Figure 5 describes the DAG of the child node *E* given the parent node *ST* at time *t*. Based on the DAG in Figure 5, we can compute *P(E)* as below:

$$P(E) = P(E \mid SC, SeC) P(SC \mid Inf, TrM, AgR) P(SeC \mid Inf, TrM, AgR) P(Inf) P(TrM) P(AgR), \qquad (5)$$

where:

- *SC*: Speed Connectivity.
- *SeC*: Security, safety, Comfort.
- *Inf*: Infrastructure.
- *TrM*: Traffic Measure.
- *AgR*: Aggregate Reinforcement.

- *P(Inf), P(TrM), P(AgR)*: the probabilities that a given WaC scheme *ST* could directly influence infrastructure, traffic measures and aggregate reinforcement, respectively.
- *P(SC|Inf, TrM, AgR)* and *P(SeC|Inf, TrM, AgR)*: conditional probability that speed connectivity and security, safety, comfort are affected by infrastructure, traffic measures and aggregate reinforcement, respectively.

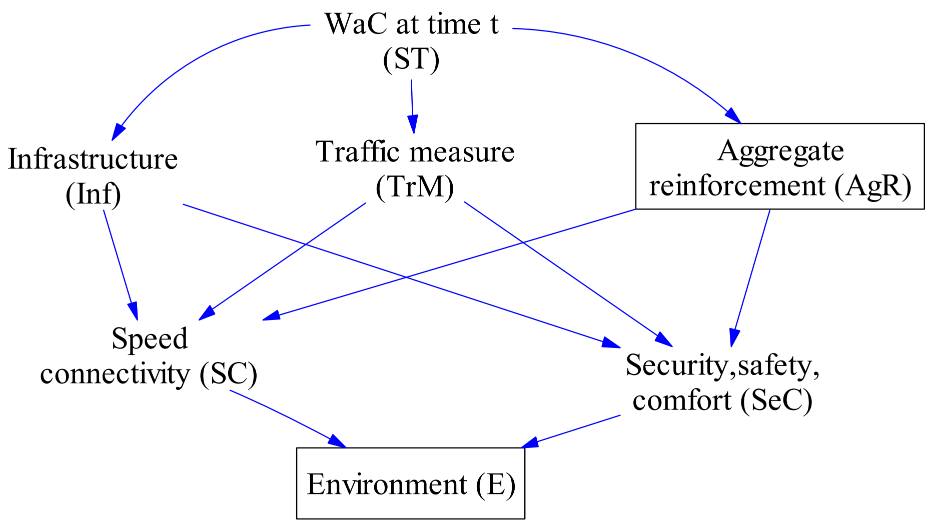

Figure 5 Causal loops to determine the *P(E)* from the WaC scheme at time *t*

Figure 6 describes the DAG of the child node *A* given the parent node *ST* at time *t*. Based on the DAG in Figure 6, we can compute *P(A)* as below:

$$P(A) = P(A \mid CP, Int)P(CP)P(Int), \quad (6)$$

where:
CP: Cycle Provision.
Int: Integration.
P(CP) and *P(Int)*: the probabilities that a given WaC scheme *ST* could directly influence cycle provision and integration, respectively.

The set of equations (2)-**Error! Reference source not found.** allows the computation of the probability *P(PWaC)* given (a) the state of the walking and cycling scheme at time *t* and (b) the reasoning underlying the relationships between factors shown in Figure 1. In Section 4, we extend the model in the current section to capture the nature of the causes and effects in the context of a dynamic decision making process.

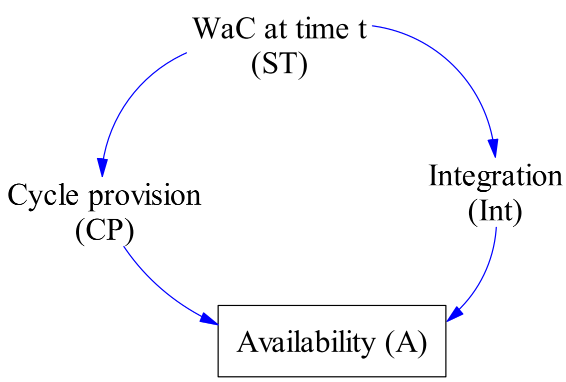

Figure 6 Causal loops to determine the *P(A)* from the WaC scheme at time *t*

4. DYNAMIC BAYESIAN BELIEF NETWORK

This section describes a model for the step-changes of the Propensity to WaC over a certain period of time, say the next 20 years. The time-step is fixed at 2 years within which the response of the people to each WaC scheme is unchanged. So we would need to determine *P(PWC)* in 10 time steps. The causes and effects model in each time interval is mathematically characterized by the BBN as in Section 3. To model the interactions of the propensity to WaC between each time interval we extend the BBN in Section 3 to the Dynamic Bayesian Belief Network (DBBN) as shown in Figure 7. It is worth noting from Figure 7 that the outcome of *P(PWaC)* at time step *t-1* will contribute to the decision to implement a further stage of the scheme at time *t*, also to the value of *P(PWaC)* at time *t*. Equation (7) describes the transitions of probability of *PWaC* between time slices as follows:

$$\begin{aligned} P(PWaC_{t+1}) = P(PWaC_{t+1} \mid PWaC_t, PCZ_{t+1}, GSN_{t+1}, A_{t+1}, E_{t+1}) \\ P(PWaC_t \mid PWaC_{t-1}, PCZ_t, GSN_t, A_t, E_t)\ldots \end{aligned} \quad (7)$$

Let *S* denote a set of discrete numbers (0,1,2,…) which represent the progress of the WaC scheme over 20 years, as indicated by the number of stages implemented. Note that *S=0* indicates the current situation. Define *dS* as being a variable which indicates whether a decision has been made to implement the next stage: it takes two values, 1 (if an implementation is to be made) and 0 (otherwise). . The dynamic equation to represent the step-changes of WaC schemes is thus:

$$S_t = \min\left(S_{t\text{-}1} + dS_t,\ N\right) \quad (8)$$

Equation **Error! Reference source not found.** indicates that if the decision factor $dS_t = 1$ the next stage will be implemented, otherwise the scheme will stay in its current state. *N* is the maximum number of stages to be implemented. The key decisive element in equation **Error! Reference source not found.** is dS_t, which is determined from the previous Propensity to WaC $P(PWaC_{t-1})$ as we can see from the causal link between the two nodes: Propensity to WaC (t-1) and Scheme (t) in Figure 7.

In this paper we adopt a simple condition to compute dS_t as below:

$$\begin{aligned} & dS_t = 1 \quad \text{if } S_{t-1} < N \text{ and } P\left(PWC_{t-1}\right) = high \\ & dS_t = 0 \quad otherwise \end{aligned} \quad (9)$$

Of course, a more realistic condition than **Error! Reference source not found.** could be made and it is worth making a further investigate on this issue in the future.

The causal loops in Figures 1-7 are implemented in VENSIM (Ventana Systems) in three layers as described in Figure 8. The model is simulated for 20 years (from 2010 to 2030) with two year time steps. Let us assume that the local authorities are planning to implement the WaC scheme in three stages (i.e. *S=0,1,2,3*) sequentially within the 20 years. The causal relationships of all factors are collected in the implementing process in order to decide what to be done next: either continue to implement the other schemes or stop.

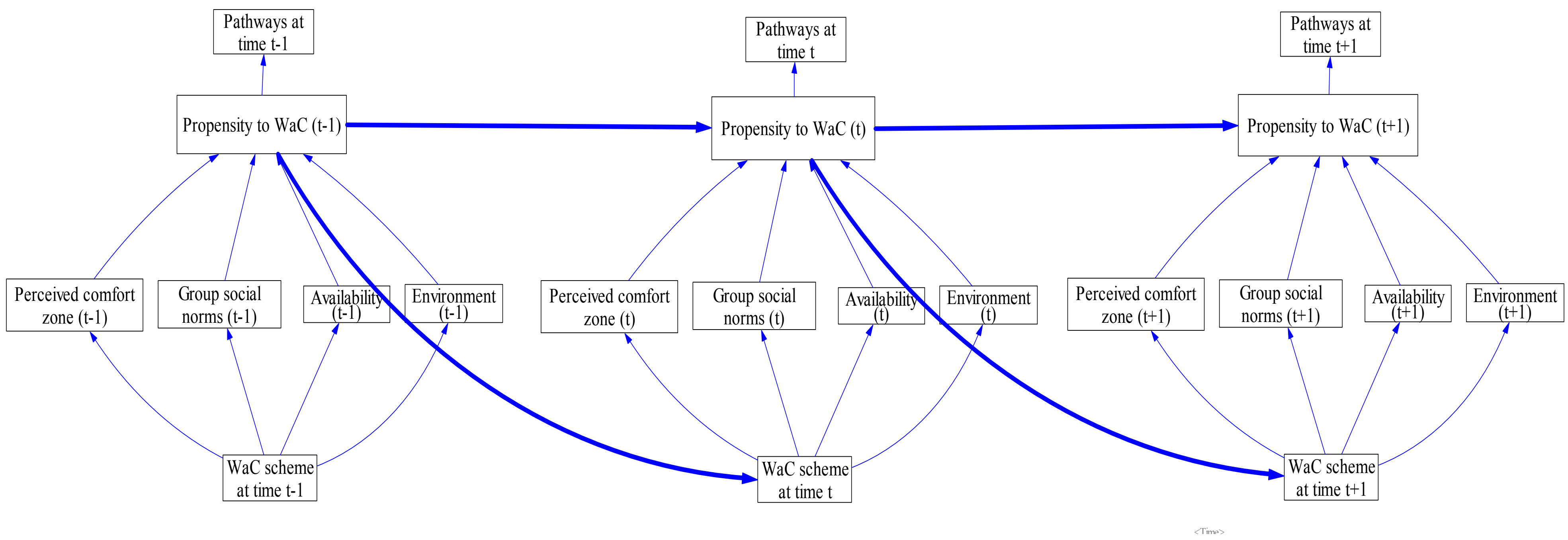

Figure 7 Dynamic BBN model for the step-changes of WaC schemes

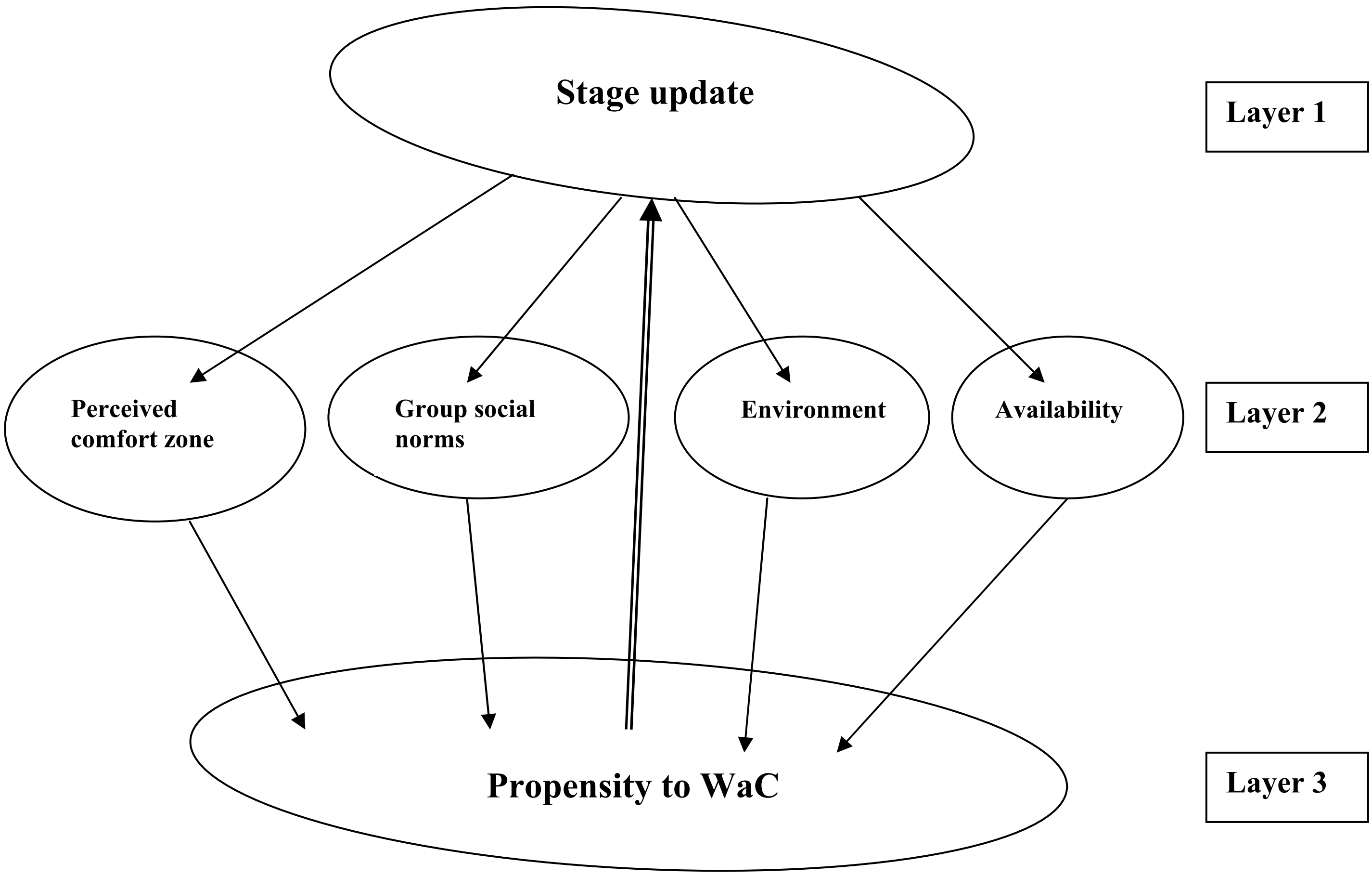

Figure 8 Implementation of the causal loops in VENSIM

Figure 9 shows the output of the model. It can be seen from the figure that there are three pathways to reach the final state in 2030, each of which is driven by many factors as indicated earlier and each pathway will happen with a certain probability.

5. CONCLUDING REMARKS

This paper has presented a method to represent the casual factors affecting the decision making process for the development of walking and cycling schemes. The proposed method has applied a novel dynamic Bayesian belief network to determine the probability to implement a walking and cycling scheme (qualitatively high, medium or low). The casual loops are facilitated through a multi-layer Vensim based model in which users can easily design the casual factors to drive the decision making process. The outcomes of the model are the pathways to a pre-determined target, each of which will happen with a certain probability computed from the causal loops. Ongoing work is being carried out to include more realistic scenarios and insightful relationships between factors in the model.

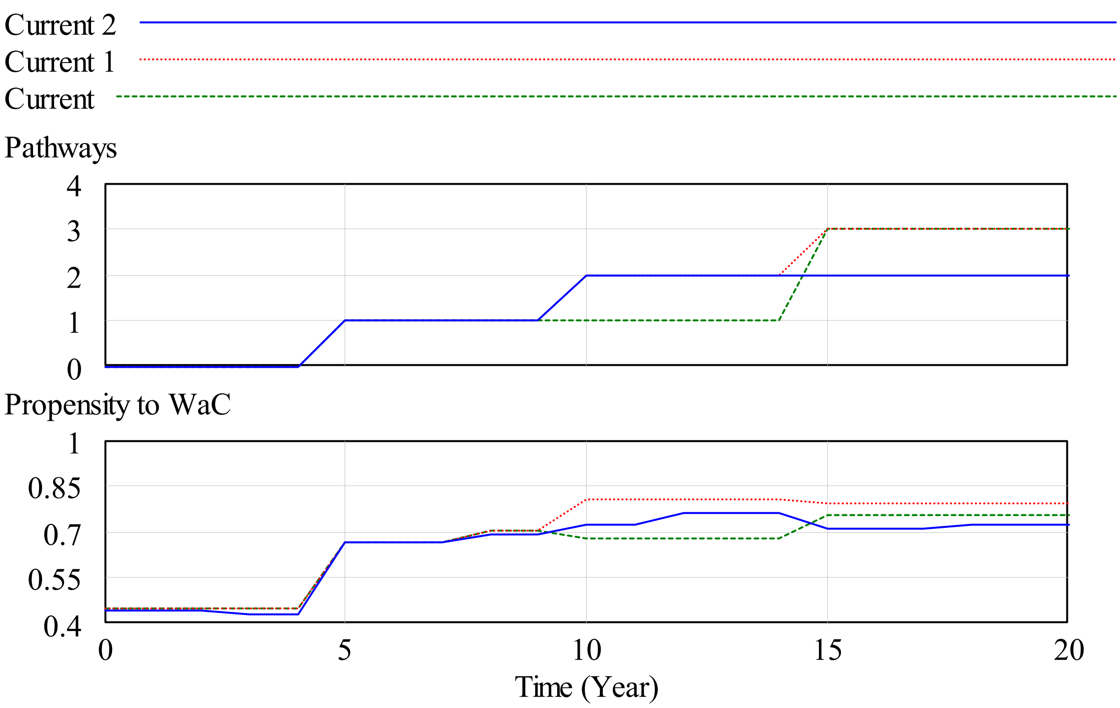

Figure 9 The development of pathways as a result of the propensity to WaC

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