future transportation

Article

Dynamic Approach to Update Utility and Choice by Emerging Technologies to Reduce Risk in Urban Road Transportation Systems

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Abstract: International research attention on evacuation issues has increased significantly following the human and natural disasters at the turn of the century, such as 9/11, Hurricane Katrina, Cyclones Idai and Kenneth, the Black Saturday forest fires and tsunamis in Japan. The main problem concerning when a disaster can occur involves studying the risk reduction. Risk, following all the theoretical and experimental studies, is determined by the product of three components: occurrence, vulnerability and exposure. Vulnerability can be improved over time through major infrastructure actions, but absolute security cannot be achieved. When the event will occur with certainty, only exposure remains to reduce the risk to people before the effect hits them. Exposure can be improved, under fixed conditions of occurrence and vulnerability, by improving evacuation. The main problem in terms of evacuating the population from an area is the available transport system, which must be used to its fullest. So, if the system is well managed, the evacuation improves (shorter times), meaning the exposure is reduced, and therefore, the risk is reduced. A key factor in the analysis of transport systems under emergency conditions is the behavior of the user, and therefore, the study of demand. This work identifies the main research lines that are useful for studying demand under exposure-related risk conditions. The classification of demand models that simulate evacuation conditions in relation to the effect on the transportation system is summarized. The contribution proposes a model for updating choice in relation to emergency conditions and utility. The contribution of emerging ICTs to actualization is formally introduced into the models. Intelligent technologies make it possible to improve user decisions, reducing exposure and therefore risk. The proposed model moves within the two approaches of the literature: it is an inter-period dynamic model with the probability expressed within the discrete choice theory; furthermore, it is a sequential dynamic model with the probability dependent on the previous choices. The contribution presents an example of application of the model, developing a transition matrix considering the case of choice updating under two extreme conditions.

Keywords: risk reduction; emerging ICT; dynamic demand models; evacuation; smart city

Citation: Russo, F.; Comi, A.; Chilà, G. Dynamic Approach to Update Utility and Choice by Emerging Technologies to Reduce Risk in Urban Road Transportation Systems. *Future Transp.* **2024**, *4*, 1078–1099. https://doi.org/10.3390/futuretransp4030052

Academic Editor: Lynnette Dray

Received: 18 July 2024
Revised: 3 September 2024
Accepted: 14 September 2024
Published: 20 September 2024

1. Introduction

Demand models play a key role in the analysis of transport systems under emergency conditions. The international literature had a notable impulse due to the very dramatic human and natural disasters at the beginning of the 21st century, including September 11 and Hurricane Katrina [1,2], and other huge disasters on other continents.

The disasters at the beginning of the millennium led all states to consider international decisions of particular importance, which led to the Sendai Framework for Disaster Risk

Reduction (2015–2030) [3] and the signing of Agenda 2030 [4], which places risk reduction within Sustainable Development Goal 11.

Analyzing the international scientific and technical literature, it is found that risk is determined by the product of three components: occurrence, vulnerability and exposure. Vulnerability can be improved through large infrastructure actions in both the civil and industrial sectors, but absolute security cannot be achieved. Events, particularly meteorological events, can be studied and predicted with a good degree of reliability. But when a probable event occurs with certainty, only exposure remains to reduce the risk for people before the effect of the event affects them.

Under fixed conditions of occurrence (event level) and vulnerability, the risk can be further reduced by reducing the exposure. The method chosen to reduce exposure is to improve the evacuation of people from the study area. The main problem when evacuating the population from an area is the available transport system, which must be used to the fullest. That is, the travel times from the places where people are to the identified safe places must be reduced as much as possible. Thus, if the system is well managed, the evacuation improves (shorter times), and subsequently, the exposure is reduced; therefore, the risk is reduced as well.

The results achieved in this century were significant. However, the main demand models developed to reduce exposure are static, i.e., they do not take into consideration that the perceived attributes and the choices are strongly influenced by the time evolution, and they do not consider the advancement of intelligent transportation. At the same time, research on transport demand models under ordinary conditions has progressed by developing dynamic models.

The demand model is one of the three pillars of transport system planning, together with the supply model and the supply–demand interaction model (assignment). The set of these three models, which forms the basis for the science of transportation systems, is defined as the transportation system model (TSM).

The demand models are based on specific assumptions and classified according to the level of choice simulated; the approach adopted to simulate the travel demand; and the basic assumptions, which can be behavioral or descriptive.

The demand models used in the TSM, within the topological-behavioral paradigm, belong to discrete choice models. These models are obtained under the hypothesis of a decision-maker's utility maximization behavior [5,6]. The specification most used to simulate the different levels of demand is segmentation of the process into four steps: generation, distribution, mode choice and path choice [7]. The demand models specified and calibrated under ordinary conditions cannot be used directly under conditions different from ordinary ones, such as those that arise in the presence of risk conditions.

A transport system under risk conditions can be modeled, maintaining the same structure as the TSM under ordinary conditions. In the presence of risk, the overall structure remains the same, but the individual models are strongly modified.

As soon as a dangerous event of any kind occurs, both the operating conditions of the supply system and the users' behavior change for different reasons: the public decision-maker intervenes and can modify the supply system (e.g., limiting the access to one or more roads) and influence the behavior of users (e.g., suggesting paths to a given destination); modification of the set of alternatives available to the user by increasing or reducing the available routes; evolution of probabilistic aspects in the formulation of choices; and modification of attributes and parameters [8,9]. The mentioned reasons do not allow direct use of the models obtained for ordinary conditions, as they require further specific advancement.

The models available in the literature and sometimes used for risk conditions are of the static type, with the assignment evaluated by deterministic or stochastic user equilibrium, DUE or SUE, models. As mentioned, these models demonstrate a serious limitation due to the case for which they are to be used, i.e., extraordinary conditions where the flow situations on each link change with respect to the consolidated knowledge of the users.

Therefore, it is necessary to propose dynamic models, which are not traditionally used for evacuation conditions. The use of dynamic models allows the analyst to determine the development of the flows on the link in the successive periods of the evacuation. The availability of tools provided by emerging information and communication technologies (ICTs) allows planners to go a step further by allowing them to provide up-to-date information to users, further reducing the evacuation times. Figure 1 schematizes the transition from the static and dynamic models available in the literature for ordinary conditions to the dynamic models proposed for the reduction of evacuation times by the analyst and then to the dynamic models with information for the user for the further reduction of evacuation times.

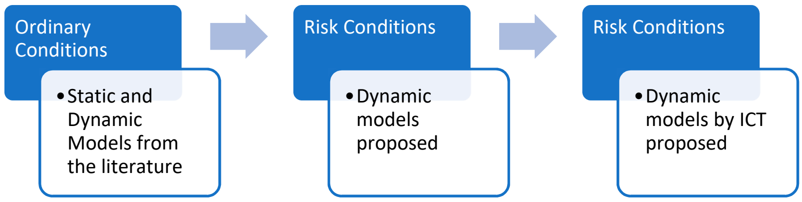

Figure 1. The literature and proposed dynamic models.

This paper is organized as follows. Section 2 presents the demand models developed for ordinary conditions that can be used to simulate transport choices under emergency conditions. Section 3 specifies the demand models in different time evolutions of risk and under dynamic ordinary conditions, while Section 4 describes the proposed model. Section 5 compares the proposed method with the traditional ones. Finally, Section 6 draws conclusions and establishes the road ahead.

The proposed study is of interest to researchers who deal with demand models under different conditions, both for the modification of choices and for the evolution processes of utility learning. The work can be useful for technicians and planners who are involved, on behalf of public or private decision-makers, in preparing or updating evacuation plans and, more generally, risk reduction plans.

2. The State of the Art

Starting from the well-known demand models developed for ordinary conditions, some models are recalled that simulate the choices of users during an evacuation. The models are specified by referring to the general four-step model used for application within the TSM.

The first set of models concerns the demand for *trip production/generation* under evacuation conditions. The most studied dangerous event, with delayed effects over time, is the hurricane. Generally, two decision-making levels for the user are considered in terms of generation: whether to evacuate (yes or no) and when to evacuate.

The models are usually of the statistical type and consider the average indicators per category. These values are specified in relation to the severity of the hurricane and obtained from the behaviors observed during the events that occurred.

Among the most interesting approaches is [10], where the evacuation behavior of a hurricane is defined on the basis of five variables: specific factors of the hurricane, the level of risk in the area, the role of public authorities, the type of home, and the perception of the personal risk.

In [11], household decision-making is investigated based on four factors: number of family vehicles; distances traveled in the evacuation; information available; and times in the network.

In [12], the use of the probit model is considered to evaluate the elements that determined the evacuation behavior of families during each storm, with reference to the territory of Florida [13]: Katrina SE, Wilma, Dennis and Katrina NW.

A specific problem that can be addressed in the generation phase is that of identifying the degree of centrality of the place where the generic user is located. Network analysis techniques can be used to define the degree of centrality [14–16]. For the vulnerability of the network, different aggregated indicators have been proposed and implemented [17].

The second group of models concerns the *choice of destination*. During an evacuation, the choice of destination can be constrained by the conditions of the flows along the links crossed; therefore, it is necessary to consider the choice of route after the destination. For the choice of destination, the work developed in the United States can be mentioned on the basis of a considerable amount of data collected during hurricane events that occurred in the 1990s of the 20th century. Among these works, the one developed with data from the post-Hurricane Floyd survey in South Carolina in 1999 can be recalled [18]. About 1800 users were interviewed in the urban areas of Charleston, Myrtle Beach, and Beaufort, South Carolina. A multinomial logit was specified with attributes relating to the socio-economic and demographic characteristics of the users, identifying the destination: toward friends and/or family members, or to hotels. It is also useful to recall the works that consider the role of public administration, including the work of Dixit [19], where different plan scenarios are compared. In the assessed scenarios, the best way to program evacuation orders is studied, verifying the capacity required by the different individual routes. In [20], a model for path choice is specified and calibrated. It is necessary to point out the model presented in [21], in which user information is explicitly introduced into the specification of the path choice model during an evacuation. The case study is the Rotterdam metropolitan area. Finally, it is worth mentioning one of the first works on the subject of evacuation, which uses a macro approach, which in many respects is still valid today, but which, evidently, does not contain the evolution related to the possibility of using ICTs [22].

The *analysis of transport systems under emergency conditions* was deepened in a research project developed at the University of Reggio Calabria. The results obtained concern the progress of the TSM under risk conditions. As part of the TSM, various models have been studied, specified, and calibrated on the basis of data obtained from real evacuations of urban centers. The models developed refer to the main works published in relation to the demand [23], supply [24–26], network design [27–31], development of a decision support system [31–33], planning methods [32,33], and training [34].

The works mentioned, in the context of what is defined as a static approach to the TSM, although offering a notable contribution to the advancement of the study of systems under risk conditions, are constrained by their real nature, which does not allow the temporal evolution of the phenomena to be explicitly considered.

The nature of the system under conditions of risk is precisely that of an evolving system, which can be modeled in the first instance with the hypothesis of stationary conditions, unless at the cost of limitations. It is therefore possible to introduce the general conditions of evolution of the system from the event to the effect on users of the risk situation, recalling in the following paragraphs the dynamic demand models proposed to date for ordinary conditions. The most advanced static model proposed for the TSM under disaster risk is the network equilibrium under adverse weather conditions [35], in which two classes of travelers are considered.

In this paper, the general formulation of risk is considered a product of occurrence, vulnerability, and exposure. This formulation is one developed internationally in the context of quantitative approaches to the study of risk. The quantitative approach is the approach used in engineering within the general framework defined for risk [36]. In the considered formulation, it clearly emerges that the study of the evolution of demand in the intervals between events and effects is decisive in reducing the risk through the reduction of the exposure.

Therefore, it is useful to present an overview of the main contributions that consider the evolution of the different components of the demand for transport under emergency conditions.

Several works have been developed on this topic, but as revealed before, in most cases, an overall reading of the system with the identification of the dynamic components of the demand is not considered. Therefore, it is necessary to synthesize models that simulate the demand in relation to the transport system. Models that address natural and human disasters are considered. Given the lack of a dynamic model for risk conditions, it is therefore necessary to start with the analysis of the dynamic demand models developed under ordinary conditions.

The problem that arises is thus that of identifying a dynamic model valid for disaster risk conditions with a delayed approach. To answer this question, an overall dynamic model is therefore proposed in which both the sequential updating process of the choices and the learning process by the user are proposed, explicating the different emerging ICTs useful to the dynamic component. In this way, the next section of this paper presents, on the one hand (Section 3.1), the main element of a temporal definition of an extraordinary condition that evolves into a specific event and a generalized effect on users; and on the other hand (Section 3.2), a brief analysis of the literature relating to dynamic demand models under ordinary conditions that can be considered within the general behavioral-topological paradigm within the TSM [7,37,38].

From these two key elements, in Section 4.1, the properties of the sequential analysis and sequential discrete choice dynamic models are described and the dynamic updating model of the user's utilities is analyzed (Section 4.2); then, a general dynamic model is proposed that explicitly models the update choice for risk conditions (Section 4.3), leaving sequential analysis and considering the use of emerging information and communication technologies, especially with regard to the Internet of Things (IoT). For modifications to the learning process and then the update utility connected to the use of the IoT under ordinary conditions, see [24,39,40] and the references therein. In Section 5, the existing literature models with which the proposed model can be compared are first reviewed. Then, the models used in the dynamic inter-period processes and the sequential models, with memory of the previous choice, are recalled. Therefore, a model application example is defined using a network structure similar to that of many territorial realities.

3. Summary of Demand Analysis in Different Time Evolutions of Risk and under Dynamic Ordinary Conditions

The problem that arises under the extraordinary operating conditions of a transport system must be studied in its various temporal evolutions. Following the US approach, given a generic risk, the temporal evolution can be categorized into four phases: mitigation, preparation, response, and recovery [39–41]. Each of these phases has a specific evolution, given by the nature of the phase.

In this study, the focus is on the mitigation phase, as the better the modeling performed in this phase, the better the results in terms of reducing the real risk in the response phase. The nature of the evolutions is different from those that describe a system under ordinary conditions.

In Section 3.1, the analyzed evolution concerns the transition from the ordinary to the extraordinary condition, verifying in which phases and how it is possible to intervene to reduce the risk, and which tools to use in each phase.

In Section 3.2, the dynamic evolutions of user behavior over time are examined, recalling, in particular, the models that allow the road system to be analyzed under ordinary conditions.

The most advanced literature in the above two fields of temporal evolution analysis allows planners to clearly define the current state of the research. In Section 4, based on what has been seen in the two above-mentioned subsections, the proposal for a model is presented that can be developed in the second part of the "mitigation" (planning) and in the "preparedness" (training and exercises) phases to evaluate the behaviors that the user will assume under conditions of "response".

3.1. Temporal Evolution of Risk Conditions

To define the model to be used in the planning (mitigation phase), it is necessary to consider the evolution of the event over time with respect to the effect on users under the real conditions (response phase).

The time evolution with respect to a specific risk can be segmented into immediate and delayed effects. The definition of an immediate or delayed approach cannot be provided in an exhaustive form, because it depends on the time that elapses between the specific event and the effect.

In this work, attention is paid to the time interval between the occurrence of the event and the beginning of the effect on the affected population. This time is used to manage the early warning and reduce the effect of an event occurring. In the literature, this time and the linked early warning are discussed by different authors with reference to different natural risks [42–44].

To identify the main milestones of temporal evolution, it is necessary to consider the three processes that evolve over time, the event process, the user behavior process, the evolutionary process of the supply, and the interaction system.

Given a specific event, the reference temporal process to be considered is the one relative to the event, considering all the times from the one at which the public decision-maker is informed about a risk determined by a possible event and decides to intervene to reduce the risk level. The main time milestones are the following:

- d_0, the public authority decides to plan to reduce the risk;
- d_1, the public authority decides to start training and exercises;
- d_2, an event occurs, the effects on the population begin, and the procedures for reducing the exposure are activated;
- d_3, a maximum effect related to the event is considered, and the exposure can no longer be reduced;
- d_4, the event no longer produces direct effects on the population;
- Δ_x, the differences between d_x and d_{x-1}.

In the hypothesis that $\Delta_3 = (d_3 - d_2) > 0$, where greater than zero means that there exists the possibility of starting an evacuation, the public authority begins the evacuation of the population before the effect reaches its maximum. In these cases, the evacuation could be implemented and run in the time interval given by Δ_3.

In the case that a delayed approach can be considered, it is possible to use the introduced time milestones to identify the temporal process relative to the planning and management of supply and interaction, which has to be organized by the public decision-maker. In this second process, the main phases in which it is possible to operate to reduce the risk considered are identified.

Regarding the introduced time milestones, the emergency planning activities, as defined at the international level [39–41], can be classified as the following:

- *mitigation*, involves the modeling, planning, and programming activities developed in relation to a hypothesized event;
- *preparedness*, involves the activities carried out to prepare the population to respond to the effects of the event; in this way, the main actions are linked to the training and exercises on which specific models can be calibrated;
- *response*, involves all the activities that allow the effects to be reduced during the event, following the indications of the plan if there exists one and of the exercises if performed;
- *recovery* (community), involves all the stages of infrastructure reconstruction after the realization of the maximum effect.

Considering the four phases, reference can be made to the formulation presented in the literature [45,46]. Parallel to the evolution over time of the event and of the system in terms of the information provided, it is possible to identify over time the evolution of user behavior. It is possible to associate three different phases with the temporal development of the event [47]:

- *pre-impact phase*, which occurs in $[d_0, d_2)$, divided into two subphases as follows
  - threat subphase, corresponding to interval $[d_0, d_1)$, in which the decision-maker prepares the plan;
  - warning subphase, corresponding to interval $[d_1, d_2)$, in which the training and exercises can increase the knowledge of the user;
- *impact phase*, which occurs in $[d_2, d_3]$, in which the user has the last time and the last possibilities to evacuate.
- *post-impact phase*, which occurs from d_3 and is divided into two subphases:
  - recoil subphase and rescue, which correspond to interval $(d_3, d_4]$, where the condition of the user depends on the public safety effort;
  - post-traumatic subphase, corresponding to interval (d_4, d_n), with d_n as the final time of the post event.

Figure 2 highlights the temporal evolutions of the decision-maker, the natural or anthropic risk, and the behavior of other users.

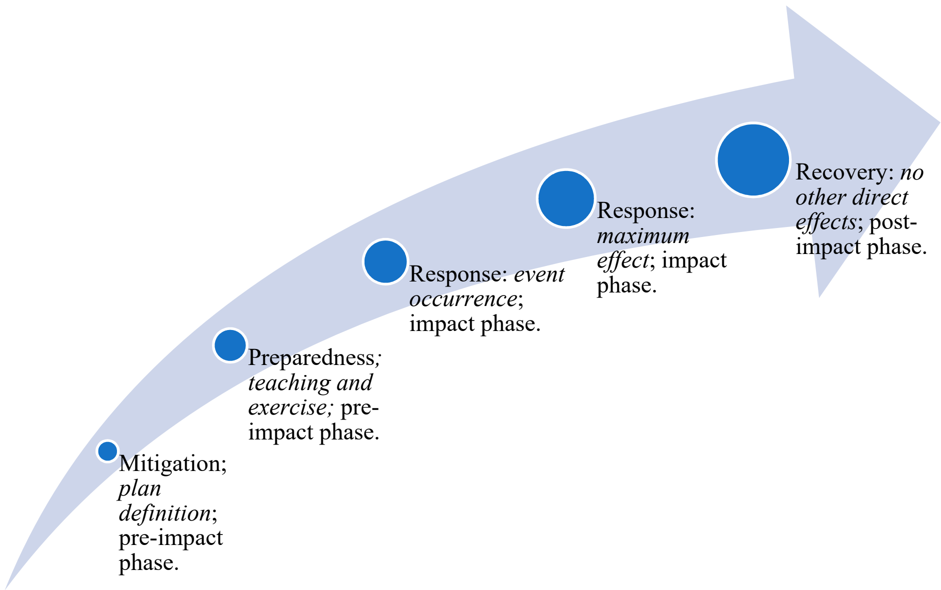

Figure 2. Main milestones: decision maker; *risk process*; and user behavior.

As mentioned before, Δ_3 is the decisive value for exposure reduction. If Δ_{3risk} indicates the real time between the event and the effect, and if Δ_{3plan} indicates the time calculated by the plan to have the population evacuated, the plan is accepted if it results in the following:

$$\Delta_{3plan} < \Delta_{3risk}$$

It is important to note that the nature of the two terms of inequality is profoundly different. Δ_{3risk} refers to the occurrence of a real event and therefore to the evaluation that specialists in that event (e.g., meteorologists or geologists) make of the time necessary for the effect to occur, i.e., they study the entire temporal evolution of the phenomenon. Δ_{3plan} refers to the evacuation time, which is simulated by the plan and as close to reality as possible. In this case, the technicians are different from the previous ones and must be traffic and transport experts.

The solution to the problem, in terms of the Δ_{3risk}, given by the inequality therefore depends on the event studied. Referring to the FEMA [45,46] classification, events can be divided into macro classes:

- meteorological (weather-related) hazards such as the following,

    - thunderstorm,
    - flood,
    - tornado,
    - hurricane,
    - winter storm,
    - drought,
    - wildfire;
- geological hazards such as the following,
    - landslides and mudflows,
    - earthquakes,
    - tsunamis,
    - volcanoes;
- transportation;
- disease;
- contamination.

In the various states, due to the specific characteristics of each country, it is possible to identify some major disasters for which exposure reduction procedures can be particularly important because they can generally occur.

In addition to the major natural and anthropogenic disasters that have occurred in the United States in the 21st century, other major disasters can be recalled for which the exposure procedures presented here could contribute to the knowledge concerning similar, future events.

After mentioning the attack on the Twin Towers at the beginning of this paper, it is necessary to mention the problem of humanitarian evacuations in war-torn territories; these evacuations are organized by the military and have no decision-making components for individual users. On the other hand, evacuations related to natural disasters are important, because they have a large temporal delta (Δ_{3risk}) and therefore can be carried out, and because they produce enormous levels of death.

Among the most significant in Asia, it is worth remembering the great earthquake of 11 March 2011 in eastern Japan. The disaster was caused by the concatenation of three tragedies: the first caused by the earthquake, which caused considerable damage, the second connected to the tsunami generated by the earthquake, and the third connected to the damage to the affected nuclear power plants: Tokai, Higashi Dori, Onagawa, and Fukushima Daiichi and Daini. The exposure reduction problem is relevant to the second and third events. A rough estimate indicates 20,000 deaths from the effects of the tsunami that spread throughout the Pacific Ocean and the Indian Ocean [48,49].

On the continent of Oceania, the 2009 Black Saturday forest fires should be recalled. In this case, residents were faced with a very serious choice between staying to defend their property from forest fires and leaving before the fire approached, leading inexorably to the loss of human life. In both alternatives, the result is dramatic, as the loss of human lives has demonstrated. Even in this case, the problem of evacuation becomes crucial [50,51].

Among the most serious natural disasters of the 21st century are those caused by the Idai and Kenneth cyclones, which occurred sequentially between March and April 2019. The territories directly affected were Mozambique, Malawi, Madagascar, the Comoros Islands and Zimbabwe, with thousands of direct deaths [52,53]. The direct event, as in the case of that in Japan recalled earlier, had the exposure problem.

3.2. Dynamic Demand Models under Ordinary Conditions

From what has been seen in the Section 1 (Introduction), it emerges that the main research directions useful for the study of demand under exposure conditions are lacking in terms of considering the conditions of dynamic choice for the user. It is therefore necessary to recall the main lines of research relating to dynamic changes under demand in ordinary conditions, because there is no deepened literature that considers extraordinary conditions.

In this way, it is necessary to recall works that consider the dynamic variations reproducible by means of a model. In the following, only some works are proposed with reference to the specific dynamic variation: attributes, parameters, random residues or distribution probabilities, and the possible combinations between the variations.

The models that analyze the modifications to the set of alternatives are not considered because their evolutionary process cannot be studied as a passage between different states.

The first dynamic component is the variation of attributes from period to period. This variation directly affects the dynamic process of utility update. In this context, one of the first developed models should be recalled: the Manski and Sherman model [54], which was subsequently developed by Train [5]. In the model, a dynamic attribute is introduced in the specification of the utility; this attribute is defined as the cost of the transition. The attribute is specified with a dummy variable that is:

- 0 if $k^{t-1} = k^t$ in time t,
- 1 otherwise.

The second dynamic component is the variation of the parameters. The models developed in the literature consider the variation of parameters among users who make choices. In [55], a model is presented that allows us to consider the distribution of parameters among individuals belonging to a given sample. The estimation is performed on different subsets of users with respect to the complete sample. The method allows one to define the form of the distribution of the parameters among several individuals, but it does not analyze the distribution over time. However, it should be noted that, with the methodology proposed by these authors, the distribution could be estimated on the basis of the user's choice behaviors as stored in different intervals of the process.

The third dynamic component to recall is the *variation of the probability function*. A prototype model was proposed in [8,56]. The model is used for the dynamic choice of the route in the case of high-frequency services. In the transit system, if t^1, t^2, ... is the time sequence of arrival of the runs, and j^1, j^2, ... is the sequence of runs, the probability of a run j^w that arrives in t^w is given by the probability of choosing j^w for the one that the users have not boarded during the previous runs.

A binary logit model has been proposed to simulate the probability of evacuation of a family in each interval of the period of time for evacuation [57]. This is one of the very few works that considers at least one dynamic component. A segmentation of the time intervals is considered. In each interval, a family can choose whether to evacuate or not. If the family does not evacuate in the given interval, the choice is reconsidered in the next interval.

In addition to models that specify a single dynamic component, models that consider several components at the same time have been developed. The model presented in [58] considers the dynamics in the discrete choice related to vehicle ownership. The model considers the evolution of the number of vehicles owned by the family and the evolution of the income of family members. The hypothesis is that the family evaluates the number of vehicles owned at regular intervals and decides whether to buy a new vehicle and increase the number, to sell one and reduce the number, or to keep the same number under the two hypotheses of no purchase and simultaneous purchase–sale. A first-order Markov process is used. The effects of past choices are evidenced using a loyalty attribute and an experience index. These attributes and their calibrated parameters differ over time. The model can only be used to reproduce the sampled situations, and it does not have a useful structure for forecasting.

A model formalizing the dynamic modifications of attributes and functions is formally presented in [7,37,38]. The model simulates the dynamic behavior in the choice of the path, considering two phenomena that are not considered in the static approach: the process of user learning with the integration of experience and updated information (utility update model); and the process of updating the user's choices, considering the choices made on previous days (model for updating the choices).

4. The Proposed Dynamic Model

4.1. The Dynamic Structure with the Two Updating Models

The dynamic process model proposed here for the study of the evolution of the system under risk conditions refers to the theoretical structures mentioned above, which are defined as inter-period dynamics [7,37,38]. These models refer to the theory of nonlinear dynamic processes, if the system is analyzed in its states with deterministic variables, and to the theory of stochastic processes, if stochastic variables are used.

The study of the inter-period dynamic processes requires the analysis of two distinct phenomena that evolve over time, which are usually treated simultaneously in the static approach to equilibrium. The two phenomena need, in the study of the processes, explicit modeling to grasp the real nature of the temporal evolution of the system.

The two phenomena to be analyzed and modeled are *utility updating* and *choice updating*. The phenomenon to be analyzed and modeled concerns how the user synthesizes the information on the utilities, and therefore on the costs, as experienced on previous days with that available in real time (*utility updating model*). The phenomenon and the model became even more central with the rapid growth of emerging ICTs in recent years. The utility updating model has been treated in the literature through the proposal of various mathematical formulations and the explicit presence of ICTs [7,25,38,59].

The choice updating model constitutes the other pillar of the study of the temporal evolution of transport systems. The phenomenon to be analyzed and modeled concerns how the user summarizes the choices made previously and how this synthesis affects the new choices that must be made.

The utility updating model mainly concerns the evolution of the supply component, which, in fact, in dynamic systems, affects how the supply is configured from one period to the next. The choice updating model mainly concerns the evolution of the demand component, i.e., how the demand model can represent the user's decision-making evolution.

With reference to the two models mentioned here, in the next subsection, the utility updating model under risk conditions will first be proposed, explicitly considering the role of emerging ICTs; then, the choice updating model, again under risk conditions, will be proposed, introducing an example of the main characteristics of the transition in the choice.

4.2. Utility Updating Process Considering the IoT

The field of emerging technologies has become increasingly popular. The level of maturity of the various emerging technologies varies greatly. In fact, some of them are already widely applied (e.g., smart sensors, connectivity technologies), although further development is expected in the next decade. On the other hand, other technologies (e.g., artificial intelligence) are potentially ground-breaking, but applications are only just starting to use them, discovering what is already possible and what still needs to be developed. Therefore, referring to the opportunity offered in terms of obtaining real-time knowledge from the network, the IoT is of high relevance.

The IoT can be represented as a set of physical objects and a telematics network that connects such things to other devices and systems.

One field in which the use of these devices has been extensively implemented is that of urban-scale deliveries. In this case, the presence of private operators and the related need to find economically advantageous solutions, connecting shippers with retailers and final consumers, drive the ever-increasing use [60,61].

In [56], the introduction of an intelligent transportation system into transportation models is analyzed to support the urban evacuation planning process. The diffusion of traffic sensors as well as vehicle detection sensors [62] allows one to update the real-time traffic conditions and to produce information for users as in the case of implementing traveler advisors [63].

Let C be the vector of the user path costs of the O-D pair ov, with entry C_k, $k \in K_{ov}$, while let X be the vector of the path attributes for users of the O-D pair ov, with entry X_k, $k \in K_{ov}$, where K_{ov} is the path choice set on the O-D pair ov

In the most general scenario, the path cost is composed of the additive costs and non-additive costs. It is reasonable to infer that only the additive costs are significant. Therefore, the path cost, under static conditions, is obtained by summing the path attributes.

$$C_k = \sum_n \beta_n \cdot X_{hk} \tag{1}$$

where X_{hk} is the attribute h of path k.

Then, the path costs on time t of day y, $C[t, y]$, are calculated as a function of the attributes related to the time t of day y, $\boldsymbol{X}[t, y]$:

$$C[t,y] = \psi(\boldsymbol{X}[t,y]) \tag{2}$$

Users can estimate such attributes through a learning process, which usually consists of evolutions of t and y [7].

The study of learning processes, and therefore of utility updating processes, is carried out in the literature (as reviewed above) for systems under ordinary conditions. The theme that arises here is verifying what are the conditions for defining the utility update under extraordinary conditions, given the presence of risk. In fact, in this case, the user's previous knowledge of the network conditions (ordinary) cannot be used, with the process on y and at t.

In the presence of risk, it is necessary to separately identify what contributions can be made to the user's updating process, with respect to the two evolutions on day y and at time t.

First, the y-based process is considered. For some attributes, it is possible to know the value experienced (tested) in previous periods in the presence of evacuation exercises or the values learned during training courses (training) carried out by the user regarding risk planning. These values can and should be used as a basis for experiential knowledge of temporal processes with respect to y. $X[y-1]$, $X[y-2]$ do not indicate the values of the days "physically" preceding day y, but of the previous ones in which the exercises or training courses were carried out.

Thus, in general, Equation (2) can be written as follows:

$$C[t,y] = \psi(X[t],\ldots,X[y-1],X[y-2],\ldots) \tag{3}$$

The learning mechanisms according to the classical approach [7], under ordinary conditions in the inter-period process, can be computed as follows:

$$X_{hk}^{fo}[y] = \gamma \cdot X_{hk}^{exp}[y-1] + (1-\gamma) \cdot X_{hk}^{fo}[y-1] \tag{4}$$

where

- $X_{hk}^{fo}[y]$ is the value of attribute h of path k planned for day y;
- $X_{hk}^{exp}[y-1]$ is the value of attribute h of path k experienced/tested on day $y-1$;
- γ ($\in$] 0, 1]) is the weight given to the experienced/tested value.

Note that considering only the additive attributes, Equation (4) expresses the cost for all the paths k as given in Equation (1).

Equation (4) can be transferred to the extraordinary conditions, exploiting the information coming from knowledge obtained during the previous evacuation drill, as well as from the data used in designing the evacuation plan, and inserted into the big data *EP_BD* (i.e., data collected during evacuation drills):

$$X_{hk}^{EP\_BD,fo}[y] = \gamma \cdot X_{hk}^{EP\_BD,exp}[y-1] + (1-\gamma) \cdot X_{hk}^{EP\_BD,fo}[y-1] \tag{5}$$

Equation (5) can be computed using *EP_BD* in a homogeneous form, both for the path used (experienced) on the day $y-1$ (e.g., evacuation drill) and for the paths k' not used but belonging to the choice set of day $y-1$, $K_{ov}[y-1]$.

The other fundamental process to consider is that which evolves in time t. In addition, for this process, it is necessary to highlight what happens under extraordinary conditions.

In these conditions, there are two types of information related to the event (exogenous to the TSM) and the traffic (endogenous to the TSM).

Given the extraordinary conditions, user learning (for both endogenous and exogenous fields) can only be achieved through information coming from the outside. Therefore, the update occurs at each time t of day y. The single tool through which the update takes place can be summarized as the IoT mentioned above. The IoT can range from those devices used for the detection of exogenous parameters to those for the detection of endogenous parameters. In this last case, the IoT allows the possibility to obtain the real-time configuration of the network.

According to the symbols and notations summarized in Table 1, on the current day y, the above Equation (2) becomes:

$$\boldsymbol{C}[t,y] = \psi(\boldsymbol{X}[t,y]) \tag{6}$$

Table 1. Symbols and notations.

y	Current day
t	Time of the day
$C_k[t,y]$	Generalized travel cost of path k on day y at time t
$\boldsymbol{C}[t,y]$	Vector of path cost whose entry is $C_k[t,y]$
$X_{hk}[t,y]$	The h-th attribute of the k-th path on day y at time t
$\boldsymbol{X}[t,y]$	Vector of path attributes whose entry is $X_{hk}[t,y]$
$X_{hk}^{real\text{-}time}[t,y]$	Value of the h-th attribute of the k-th path on day y at time t
$X_{hk}^{fo}[y]$	Value of the h-th attribute of k-th path on day y
$X_{hk}^{exp}[y-1]$	Value of the h-th attribute of the k-th path experienced/tested on day $y-1$
γ ($\in$]0,1])	Weight given to the experienced/tested value
$X_{hk}^{IoT}[t,y]$	Value of the h-th attribute of the k-th path on day y at time t obtained through the IoT
$\boldsymbol{X}^{IoT}[t,y]$	Vector of path attributes whose entry is $X_{hk}^{IoT}[t,y]$
$X_{hk}^{EP\_BD,fo}[t,y]$	Value of the h-th attribute of the k-th path on day y at time t forecasted using previous experiences (i.e., without information from the IoT)
$X_{hk}^{EP\_BD,\,exp}[y-1]$	Value of the h-th attribute of the k-th path on day $y-1$ experienced/tested using previous experiences (i.e., without information from the IoT)
ξ ($\in$]0,1])	Weight given to the forecasted value

To draw attention to how real-time data—made possible by the IoT—affect the cost attributes (that is, how the cost attributes depend on the technology that is accessible and then on the knowledge that is both endogenous and exogenous that the technology produces), and subsequently, to highlight the impact of real-time information on the cost attributes (i.e., the dependence of the cost attributes on the available technology and subsequently on the endogenous and exogenous knowledge they produce):

$$\boldsymbol{X}[t,y] = \boldsymbol{X}^{IoT}[t,y] \tag{7}$$

Finally, the complete user learning process that allows past (*EP_BD*) and real-time information (*IoT*) to be joint gives the value of X_{hk} at time t of the current day y, joining Equations (5) and (7) (Figure 3):

$$X_{hk}^{fo}[t,y] = \xi \cdot X_{hk}^{EP\_BD,fo}[t,y] + (1-\xi) \cdot X_{hk}^{IoT}[t,y] \tag{8}$$

where

- $X_{hk}^{IoT}[t,y]$ is the value of X_{hk} at t of y; this information is made available via the IoT and shows how the network performance is evolving at the moment. For instance, it can show the travel time (X_{hk}) that other vehicles are testing out on day y in order to travel at time t on the same path k. Note that this information is updated for each time t across the entire network;
- $X_{hk}^{EP\_BD,fo}[t,y]$ is the value of X_{hk}, provided by *EP_BD* at t of y, as derived from Equation (5);
- ξ(∈]0,1]) is the weight assigned to the value without real-time information provided by *EP_BD* at time t of day y; in Equation (8), the value of ξ is considered fixed but it can also be viewed more broadly as a variable with t, shifting to 0 for the link where the vehicle is traveling (i.e., user is experimenting with a real-time value).

Classical Formulation	**Proposed Updating Learning Process Formulation**
$\boldsymbol{C}[t,y] = \psi(\boldsymbol{X}[t,y]) \rightarrow \boldsymbol{C}[t,y] = \psi(\boldsymbol{X}\,[t], \ldots \boldsymbol{X}[y-1], \boldsymbol{X}[y-2])$ Within day $X_{hk}[t,y] = X_{hk}^{real-time}[t,y]$ Day-to-day $X_{hk}^{fo}[y] = \gamma \cdot X_{hk}^{exp}[y-1] + (1-\gamma) \cdot X_{hk}^{fo}[y-1]$	$\boldsymbol{C}[t,y] = \chi(\boldsymbol{X}^{IoT}[t,y], \boldsymbol{X}^{EP\_BD}[t,y])$ Within day $X_{hk}[t,y] = X_{hk}^{IoT}[t,y]$ Day-to-day $X_{hk}^{EP\_BD,fo}[y] = \gamma \cdot X_{hk}^{EP\_BD,exp}[y-1] + (1-\gamma) \cdot X_{hk}^{EP\_BD.fo}[y-1]$ $\Downarrow$ $X_{hk}^{fo}[t,y] = \xi \cdot X_{hk}^{EP\_BD,fo}[t,y] + (1-\xi) \cdot X_{hk}^{IoT}[t,y]$

Figure 3. Comparison between the classical and proposed learning processes updating utility.

Equation (8) can be considered a reference explanation of Equation (2), which is instead written in a completely general way. We finally have the following:

$$C_k[t,y] = \psi\left(X_{hk}^{fo}[t,y]\right) \tag{9}$$

Figure 3 summarizes the comparison between the classical and proposed learning processes for updating utility. It shows that the information coming from the IoT (real-time status of the network) and BD (information coming from previous experiences) jointly allows the learning approach to be updated.

4.3. Choice Updating Process Considering Sequential Analysis

The literature presented in the earlier sections considers the dynamic demand models used in the analysis of transport systems working under ordinary conditions. This section examines the choice process under risk conditions.

No dynamic path choice model is available in the literature under risk conditions, to the best of the authors' knowledge. Consider that the choice of path is the most important because it is supported by the IoT and can really save people, but at the same time, it is the most complex due to the considerable quantity of path alternatives that are available to the user.

The general framework is first considered, then a dynamic choice updating model is proposed that can be directly applied in the case of a given and defined choice set of alternatives.

Methodologies have been developed that make it possible to analyze the detected data concerning a phenomenon, highlighting its fundamentally dynamic characteristics. A good approach is that of sequential analysis. This analysis has been developed to study evolution phenomena in sociology.

Sequential analysis allows planners to select the data concerning a user behavior process to demonstrate how to record the observation data related to the user behavior, identifying a method that allows verification of whether there are significant sequential characteristics [64].

The first element of the definition is the length of the single time interval in which it can be possible to consider the demand static. But in two or more intervals, the choice can change. In this context, the lag is defined as the number of intervals between the considered one and the others that generate the conditionality. The lag is the discriminant element of the process. In general, it is assumed that the lag is of value 1. That is, the processes only refer to the previous interval.

The main problems facing analysts are as follows:

- to verify whether the transitions from an earlier state to a later state are significant, that is, if they differ from the possibility that the two states are independent;
- assuming that the transitions are significant, to determine how much is the lag of the process.

The first decision for the analyst is how to aggregate the data collected. In a schematic way, there exist two possibilities to detect the data:

- by time interval, then fixed interval and free number of events in the interval;
- per event, and therefore, a fixed number of events and free time interval width.

A coding scheme can be developed, defining the correspondence between the observed data types and the choice alternatives, setting the maximum number of alternatives (K) and the length of the sequence (s) in terms of the event or interval.

By entering the times of occurrence of events in the database, it is possible to extract different representations from the same recorded data using an analysis by events or by intervals.

To formalize the general sequential model considering a sequence of events, a matrix of the frequency of events can be defined. It is a matrix with the same number of rows and columns; the element φ_{ij} identifies the frequency with which the event j follows the event i in the sequence of intervals studied. In the same way, the frequency matrix of lag 2 can be established, in which the generic element identifies the frequency with which event i, which occurs in the time interval $t-2$, is followed by an event j in the time interval t. It is easy to see that in the same way, the frequency matrix relating to the generic lag L can be established, where the element φ_{ij} represents the frequency with which the event i, which occurs in time t-L, follows the event j at time t. From the frequency transition matrix $\boldsymbol{\varphi}$, the *transition probability matrix* $\boldsymbol{\pi}$ of an equal lag can be obtained. The generic element of the transition probability matrix is obtained, in the first approach, by dividing the value φ_{ij} by the sum of the values of the row i. The sum of the values of each row of $\boldsymbol{\pi}$ is equal to 1.

The probability that, given event i, the target event j will occur immediately after (lag 1), or just two intervals after (lag 2), can be written, respectively, as follows.

$$\pi[j_{+1}/i_0],\ \pi[j_{+2}/i_0] \tag{10}$$

In real cases related to transport systems, the hypothesis is that the width of the intervals can be chosen in order to have only one event within the interval.

In general, in transport systems, it can happen that there are several intervals in which choices do not take place. In this case, in relation to the phenomenon being studied, the intervals without choices being made can be eliminated or be inserted into the main interval in which a choice is made.

With these conditions, it is possible to analyze the sequences with respect to the transition probabilities, leaving aside the transition frequencies.

The probability that an event will occur for a user can be studied as a conditional probability. It is highlighted that the probability that a specific event occurs with respect to a set of events is called the unconditional probability, while a conditional probability is the probability that a specific event occurs with respect to another given event.

A transition probability is defined as a particular type of conditional probability in which the probability of an event is conditioned to the event that occurred in the previous interval. Therefore, by analyzing the data relating to the sequences of event–interval pairs, it is possible to study the trend over time.

Unlike other interpretative models of the dynamic updating of choices, the sequential model allows planners to carry out analyses based on the available data structures to verify the existence of a sequential nature with its specific characteristics.

In sequential analysis, the basic idea is to reduce the uncertainty by means of knowledge of past events. To evaluate the quality of the reduction, it can be useful to implement specific tests on the obtained experimental data [64,65]. The tests to be implemented are as follows:

- *significance*, which refers to the statistical significance of the sequences obtained related to lag 1 to be evaluated;
- *stationarity*, which refers to the sequential structure of the data, verifying if it is the same regardless of the start interval to be evaluated;
- *homogeneity*, which allows for whether the sequential structure of the data is identical among all the subjects belonging to the study set to be evaluated.

It is possible to structure the operations to be carried out to verify the applicability of a sequential model. The operations can be divided into two main parts, i.e., the former is relative to the organization of the data, while the latter concerns the tests of the existence of a sequential nature.

On this basis, it is possible to study a dynamic sequential discrete choice model. Therefore, the hypotheses are of a model developed in the context of the theory of discrete choices, with dynamic characteristics that are of a sequential type.

In the context thus defined, it is assumed that the basic data are the alternative chosen for each interval, and the attention is therefore placed on the evolution of this choice as the intervals follow one another. The data to be analyzed must, therefore, be collected in each time interval considered and must be stored as sequences of chosen alternatives (or more generally, as behavioral states).

The three tests of the sequential analysis can be performed on these data. In the case where the tests confirm the existence of an underlying sequential structure, it is possible to hypothesize an interpretative dynamic sequential model.

The central element that represents the evolution process of the choice among the available alternatives is the transition matrix. As previously mentioned, each row of the probability transition matrix represents the probabilities of switching—or not—from one alternative, defined by the row, to each of the other available alternatives, for all the users who have made the same choice given in the previous period and for the lag considered. For each row (alternative), it is, therefore, possible to specify and calibrate a behavioral model belonging to the discrete choice model class.

The dynamic sequential discrete choice model is then defined in the context of discrete choice models, with the properties of the sequential analysis and the choice alternatives relative to the previous periods.

The model defines a special class of dynamic models, which provides the probability of choice based on the condition of the current and previous systems, thus introducing a direct link between the system and the decisions previously assumed.

The probability that user n will choose the generic alternative j^t in t, $j^t \in S^t$, conditional upon the probability that user n has chosen the generic alternative j^{t-1} in $t-1$, $j^{t-1} \in S^{t-1}$, is defined as a discrete choice sequential dynamic model. This is defined as the transition probability and given by the following:

$$P^{n,t}[j^t/j^{t-1}] = prob(U^{n,t}[j^t] > U^{n,t}[i^t]\forall j^t, i^t \in S, j^t \neq i^t)/ \\ prob(U^{n,t-1}[j^{t-1}] > U^{n,t-1}[i^{t-1}]\forall j^{t-1}, i^{t-1} \in S, j^{t-1} \neq i^{t-1}) \quad (11)$$

subjected to the following assumptions:

- a physical alternative can modify the value of the attributes/parameters from $t-1$ to t, and then j^t can be equal, or not, to j^{t-1} with j^t, $j^{t-1} \in S^t$;
- S^t is equal to S^{t-1} ($S^t \equiv S^{t-1} \equiv S$), with the condition that both contain the same identical alternatives, permitting the alternatives to change attributes and/or parameters from $t-1$ to t; if $S^t \neq S^{t-1}$, a strong modification happens in the system because there is a new alternative born from $t-1$ to t; this discontinuity cannot be represented as a sequence.

In general, it is possible to model the probability that user n chooses the generic alternative $z^t \neq j^t$, $z^t \in S^t$, conditional upon the probability that user n has chosen j^{t-1} in $t-1$, $z^{t-1} \in S^{t-1}$.

5. Proposed Dynamic Sequential Inter-Period Model: Comparisons with Existing Methodologies and Case Study

This section describes the application of the proposed model to a test case, extracted from a real situation, first recalling the existing methodological approaches and developing a synthetical critical analysis, thus defining the characteristics of the proposed model.

The structure of the path choice models studied in the literature is based on the definition of a set of alternatives. In the literature, dynamic inter-period models [7,37,38] estimate the probability of choosing the individual path in each period, irrespective of the path chosen in the previous period. The use of dynamic macro- or mesoscopic models induces the need to simulate the behavior of the system by reproducing its evolution over time. Specifically, in the supply models, the algebraic relations that correlate the variables in play are replaced by differential equations or by the need to study the flow in packets [66]. The difference is given by the actualization time of the choice within the dynamic process. In the literature models, the time is given by day y, while in the proposed model, it occurs in the time period where the updating of the information occurs thanks to the IoT. The proposed model aims to remain within the dynamic inter-period models by introducing the influence of choices made in previous periods. Therefore, the definition of this area is the first comparison with the existing path choice models.

The second theme of the comparison, as found within the existing literature, is with the models of the sequential type, which consider the choice of the period t based on the chosen period $t-1$. There are multiple models in the literature, but they are all applied to cases strongly different from the choice of path. Significant are the models proposed for the study of the purchase or ownership of cars [6,57], where the choice in the period $t-1$, usually the class of car previously purchased, influences the choice in the period t, usually the class of the car subsequently purchased. Typically, sequential models move within Markovian transition matrices, as expressed with fixed probability values for each transition type. In the proposed model, instead, the probability can be modified.

The proposed model therefore moves within the two approaches present in the literature and here synthetically recalled: for which, on the one hand, it is an inter-period dynamic model, with the probability expressed in the discrete choice theory; and on the other hand, it is a sequential dynamic model with the probability depending on the previous choices. Different sequential inter-period dynamic models can be defined with the evolution regarding attributes, parameters, or random residuals, starting from the model formalized in Equation (11).

To exemplify the proposed model, a test case is presented. The case study designed and studied here refers to a real situation in which there are two parallel roads, arranged along the main evacuation direction. It is assumed that the two roads have different levels of geometric and functional characteristics: one with better characteristics and that is therefore naturally more attractive, and one with less good characteristics than the first one. The condition thus expressed is applicable to various pairs of parallel streets usually present in cities. Therefore, a main road is always accompanied on the sides by a secondary road. Usually, in a direction perpendicular to the two roads considered, there are other roads of different levels that allow the interchange between the two roads that move along the main evacuation route. The operating condition can be given by a motorway—highway pair, or highway–primary, or primary–secondary, and thus continuing for commercial and finally residential streets. In the case of tests, the one with the best characteristics is indicated as the primary road, and the other as the secondary road.

Figure 4 shows a graph of a network in which, for simplicity, the link cost is always unitary. It is assumed that the user must go from *Origin* (*O*) to *Destination* (*D*), and that there are two main roads available, one with primary characteristics (Primary road, *U*) and one with secondary characteristics (Secondary road, *S*). There are junctions in the network that interconnect these two axes.

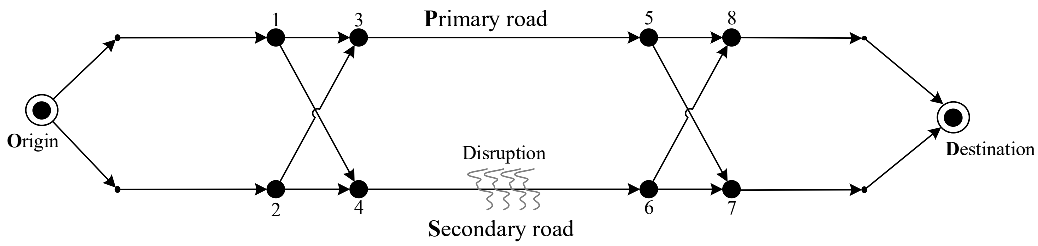

Figure 4. Network test.

At junctions, users can decide to change the axis used up to that point. To move from O to D, there are therefore eight routes (paths) available.

The frequency and therefore the probability of transition from road *S* to road *P* are analyzed considering all the routes available to the user, and vice versa. That is, the probability that a user coming from *S* goes to *P* or stays in *S* is calculated, as is the probability that a user coming from *P* stays in *P* or goes to *S*.

To highlight how the transition matrix changes as the situation in the network and the information available to users' changes, two cases are considered:

1. all available paths have the same probability of being chosen (no real-time information for users);
2. users receive real-time information on a link disruption when at nodes 1 and 2;

In both cases, eight users travel from O to D, one for each path.

In the former case, all eight paths are equally probable. In this case, the transition matrices (in terms of the frequency and probability) are shown in Figure 5 (case 1).

Therefore, we consider a second case in which information is provided to the user via the IoT when at node 1 or at node 2. The information is that links 4–6 could be interrupted due to a calamitous event. This information changes the user's choices and therefore the transition matrices. The change occurs in relation to the update utility model used. According to the hypothesis that all users only consider the IoT information when they are at nodes 1 and 2, and that they all decide not to proceed along the *S* road axis, but that they all decide to stay or to go to *P*, the transition matrices change as in Figure 5 (case 2). In fact, the two users that are at node 2 choose to go to *P* (i.e., from node 2 to node 3); similarly, the users at node 1 continue to travel on the *P* road axis. After such a choice, at the next diversion (transition) node, they continue to travel on *P* or on *S* according to the choice made before the disruption information, e.g., if users reached *D* from *S*, when at node 5, they will opt to go to node 7.

Case 1

Frequency matrix	**P**	**S**
P	4	4
S	4	4

Probability matrix	**P**	**S**
P	0.50	0.50
S	0.50	0.50

Case 2

Frequency matrix	**P**	**S**
P	8	4
S	4	0

Probability matrix	**P**	**S**
P	0.67	0.33
S	1.00	0.00

Figure 5. Network test case: transition matrices in the equiprobable case and disruption of one link.

In the equiprobable case, it is easy to see that each user has made two choices along the path between P and S, and therefore sixteen choices are obtained. In the case of user information, four users are not interested because they do not choose the links 4–6 in their path; four users, however, are forced to choose differently, moving to F; this leads to the result shown in Figure 5, case 2.

In the proposed example, the eight route alternatives, having to choose in time t and not on day y, are summarized in the two alternatives present at each intersection, namely P and S. The model, in the example, can be specified and calibrated for real cases.

The transition matrix across the entire choice set would be an 8×8, but, as mentioned, it would provide the transition of all the paths with respect to y. With the schematization introduced, the transition occurs at time t.

It is interesting to note the sensitivity of the model to information, moving from the equifrequency coming from P or S to moving to P or S (four for each transition), to a different frequency of coming from P going to P (eight) or S (four) and coming from S can only go to P. This result mathematically highlights the information provided to users with a possible (certain) interruption of links S 4–6.

The formalization proposed for the sequential inter-period dynamic choice model with the probability conditioned by the choice made in the previous period, together with the exemplification presented, allows planners to consider the proposed model a valid line of research development, which can provide fruitful results even when included in the study of the conditions of ordinary operations of a transport network.

6. Conclusions

It is possible to summarize some of the main elements of the proposed work and identify the main lines for the advancement of the research. The first element is the recognition of the demand models in the literature that deal with evacuation conditions. From this analysis, it emerges that, in most cases—in all the paths—the models are specified for a dangerous event and do not allow the analysis of the dynamic components. Generally, models that refer to large databases, such as those for hurricanes, are descriptive and therefore do not allow analysis of behavioral choices under emergency conditions.

On the other hand, various dynamic models for ordinary conditions have been developed. Starting from these considerations, in this article, a risk condition due to a dangerous event is considered and, with respect to this condition, a behavioral model of transport demand is proposed, which explicitly considers the evolution with effects in space and time. The model is specified in terms of the two main components of updating the choice and updating the utility, and an example of application for the proposed model is reported.

The greater level of attention, in this note, is paid to the model of updating choice, while the model of updating costs is only introduced, with different examples available in the literature. The model proposed for the choice, compared with the existent literature, combines two different elements: on the one hand, the need to have a memory of the choice made previously, a typical element of sequential dynamics; and on the other hand, the need to have a change in the probability of alternatives, an element of interpersonal dynamics.

This paper has presented an example of application of the model using a network structure typical of many territorial realities, with two extreme conditions of probability. In the future, it will be possible to specify, calibrate and validate a behavioral model. Models can be calibrated with both data from evacuation simulations and data concerning the stated preference type.

In a general view, the presented work can be interesting for technicians that work on risk reduction plans, considering the risk linked with events of different danger degrees, ranging from those that have a high probability of occurrence and reduced impact, such as the transport of dangerous goods, to those that have a high impact and a low probability of occurrence, such as hurricanes and, more generally, climatic events.

Author Contributions: Conceptualization, F.R., A.C. and G.C.; methodology, F.R., A.C. and G.C.; software, F.R. and A.C.; validation, F.R., A.C. and G.C.; formal analysis, F.R., A.C. and G.C.; investigation, F.R., A.C. and G.C.; resources, F.R.; data curation, F.R. and A.C.; writing—original draft preparation, F.R., A.C. and G.C.; writing—review and editing, F.R. and A.C.; visualization, F.R. and A.C.; supervision, F.R.; project administration, F.R.; funding acquisition, F.R. All authors have read and agreed to the published version of the manuscript.

Funding: This study was carried out within the research project "RISK: Recovery Increasing by Social Knowledge"—2022B4TT2M (CUP C53D23004800006), PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) Missione 4 "Istruzione e Ricerca"—Componente C2, Investimento 1.1 "Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale (PRIN)", D.D. n. 104 del 2 febbraio 2022, ERC SH7 "Human Mobility, Environment, and Space". This paper reflects only the authors' views and opinions, and neither the European Union, the European Commission nor the Italian Ministry of the University and the Research can be considered responsible for them. The APC was funded by MDPI.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors wish to thank the anonymous reviewers for their suggestions, which were most useful in revising the paper.

Conflicts of Interest: Author Giovanna Chilà was employed by the municipality of Motta San Giovanni. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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