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Optimal planning of distributed energy resources for sustainable road tunnels under uncertainty

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A R T I C L E I N F O

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A B S T R A C T

The problem of road tunnel energy consumption and sustainability is considered in this paper. To reduce energy costs and to improve sustainability, a Microgrid (MG) with distributed energy resources including renewable generators and storage systems is proposed to supply the typical loads of road tunnels. The proposed MG is modular in the sense that sets of individual modules for the solar and wind generators, as well as the batteries, are considered for the installation, while the number of modules is obtained from the resolution of a long-term planning optimization problem. A new optimal probabilistic approach that calculates the number of modules maximizing the Net Present Value (NPV) to evaluate the profitability of the MG investment is proposed. The proposed procedure includes an advanced long-term Markov Chain (MC) based methodology to generate scenarios of stochastic processes modeling all the uncertain variables involved in the planning procedure, satisfies technical and contractual constraints selectable by the tunnel owner, and implements the decision criteria most frequently applied for the selection of the optimal solution. In the numerical applications, the results obtained in different case studies show the benefits, the flexibility and the effectiveness of the proposed procedure. In fact, the modular solution allows the application of the proposed approach to a generic road tunnel located in any geographical area optimizing the use of the distributed resources.

1. Introduction

ROAD tunnels are among the most energy-intensive mobility infrastructures. They are strategically placed along roadways, including in urban areas, to reduce land use and improve the road layout. The energy consumption of tunnels, driven by lighting systems, air ventilation systems and auxiliary devices, results in high costs and significant environmental impacts. A substantial portion of this energy is used by lighting systems, which presents the most challenging optimization problem in balancing safety and sustainability. The need for improvement of efficiency and reduction of environmental impacts have prompted studies into the possibility of sustainable tunnels powered by distributed energy resources including renewable energy sources (RES). For example, [1] explores the feasibility of meeting lightning systems' energy needs with local photovoltaic systems, with a specific case study in Switzerland. However, the concept of implementing a microgrid (MG) to develop the tunnel supply system has not been considered. Numerous publications on MGs have demonstrated their effectiveness in enhancing sustainability and efficiently integrating RES [2]. While many applications have been documented, mobility infrastructures have rarely been addressed, with a few exceptions [3]. Recently, the possibility of creating an MG for supplying a sustainable tunnel [4] has been the main topic of a research project.

The MG planning, aimed at optimizing the sizes of installed distributed energy resources (DERs), such as photovoltaic plants (PVs), wind plants (WTs), and battery energy storage systems (BESSs), is crucial given the substantial capital investment and the complex relations between economic, technical and reliability aspects, sometimes reducing the dependence on the grid. This planning problem is a complex task since it should consider not only the investment costs, mainly related to

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the sizes of DERs, but also the operational costs consequent to the actual management of DERs, in particular the charging/discharging strategies of BESSs. One further point of attention is the intertemporal constraints usually introduced by the storage systems.

Conventional MG planning has historically relied on deterministic models. However, many studies demonstrated that approaches able to address uncertainties are more adequate due to the growing prevalence of uncertain parameters, variables and data inputs [5–8]. Optimal planning of DERs can facilitate the economically viable and reliable expansion of MGs, particularly in uncertain environments.

The challenge of uncertainty arises from various factors that can significantly impact the performance of the MG. The most important sources of uncertainty are due to the variability of RESs (mainly solar and wind power), the load demand, the grid connection as well as the economic factors (electrical energy prices and/or tariffs, subsidies, interest rates and so on).

To address the uncertainties in MG planning, adequate and effective methodologies must be identified and applied. Among the most used approaches (related to general applications of MGs without reference to tunnel environments) we can mention Robust Optimization [9,10], Stochastic Optimization [11,12] and Scenario-Based Optimization [7, 13]. The latter approaches are typically the most commonly used: the random features of the model are represented in terms of several realizations, and the true distribution of the optimization problem solution is approximated from the collection of the solutions calculated on the selected scenarios. The related approaches to generate scenarios of the involved random variables are based on long-term probabilistic prediction methodologies and/or with synthetic data generation [14–16]. Among them, methodologies based on Markov Chains (MCs) [14,17] are often used for the generation of scenarios, although they require particular attention in order to guarantee consistency and coherence among the real data and the generated data through the long time horizons.

In this paper, an optimal planning procedure to design the DERs installed for supplying a sustainable tunnel is proposed. The proposed MG is modular in the sense that sets of individual modules for the PV and WT, as well as the BESS, are considered for the installation, while the number of modules is obtained from the resolution of the long-term planning optimization problem. A probabilistic approach is applied to consider the sources of uncertainty of the variables involved in the planning task. In particular, the proposed procedure: i) includes an advanced long-term MC-based methodology to generate scenarios of stochastic processes modeling all the uncertain variables involved in the planning procedure; ii) optimizes the BESS, PV and WT sizes within the modular approach, aimed at maximizing the NPV under each scenario satisfying technical constraints (e.g., in terms of area available for the installations and BESS lifetime), contractual constraints (e.g., in terms of withstanding the contractual power), and security constraints (e.g., in terms of guaranteeing minimum levels of the energy stored in the BESS to possibly entirely supply the tunnel during unavailability of the upstream distribution network to improve the reliability and safety operation of road tunnel), all selectable by the tunnel owner; and iii) implements the decision criteria most frequently applied for the selection of the optimal solution that will be implemented.

The main contributions of the procedure proposed in this paper are: i) the development of a planning procedure based on a modular selection of the power supply system for a road tunnel MG, which makes the procedure completely general and applicable to all types of tunnels at any general location, increasing the use of the distributed resources; ii) the presentation of a comprehensive methodology that incorporates the sources of uncertainty of the related variables involved in the planning task and the technical and contractual decision constraints during the planning stage; iii) the application of a dedicated MC-based methodology for the generation of long-term scenarios of the variables that must be represented with a dense time resolution through the investment plan; iv) the finalization of the planning stage through the integration of the decision making process, that gives the tunnel owners the possibility to select the alternative best suited for their needs and for their risk aversion.

It is here highlighted that, to the best of our knowledge, this paper shows the first application of a long-term planning procedure to the power supply system, including RESs and storage systems, for a road tunnel MG.

The paper is organized as it follows. Section II presents the proposed optimal planning procedure, with details of the MC-based methodology for the scenario generation, of the optimization problem, and of the decision-making process based on different criteria. Section III shows the results of numerical applications based on real-world data and tunnels. Conclusions are drawn in Section IV.

2. The proposed optimal planning procedure

Let’s consider a modular DER system for a sustainable tunnel that includes Photovoltaic generators (PV), Wind Turbines (WT) and Battery Energy Storage Systems (BESSs). The general circuit of the proposed modular supply system is reported in Fig. 1. The system is considered modular in the sense that the nominal sizes of the single module for the solar and wind generators and for the batteries are fixed, while the number of modules can vary and are obtained from the resolution of the planning optimization problem. The modules of WTs, PVs and BESSs are fixed not only in terms of nominal size but also in terms of occupied surface, cost and other additional technical specifications provided by the manufacturers.

Under these assumptions, the decision variables of the planning optimization problem are: the number N_{WT} of WTs, the number N_{PV} of PVs, and the number N_{BESS} of BESS modules. The proposed optimal planning procedure is aimed at calculating the values of these variables that maximize the Net Present Value (NPV), which is a well-known economic indicator used to evaluate the profitability of a project or investment.

The scheme of the proposed optimal planning procedure is

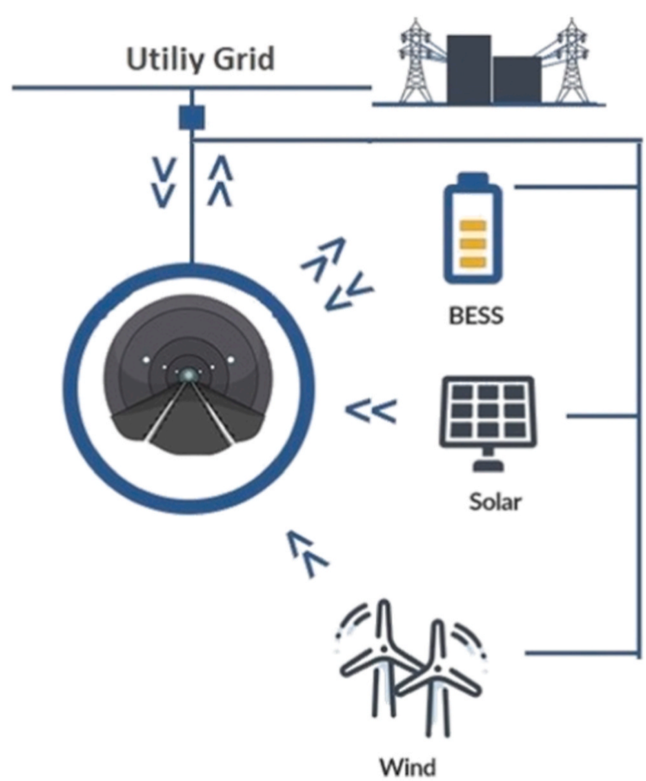

Fig. 1. Simplified scheme of the proposed MG for road tunnels.

illustrated in Fig. 2. It consists of three stages.

The first stage involves the generation of l^* scenarios of the stochastic processes modeling all the uncertain variables involved in the planning procedure. As detailed below, some variables must be characterized by long-term scenarios having a dense time resolution (i.e., one hour), while other variables must be characterized by long-term scenarios having a low time resolution (i.e., one year). Due to its increased complexity, the generation of scenarios for the former variables is performed through a dedicated Markov Chain (MC) based methodology, while the generation of scenarios for the latter variables is performed through a simplified procedure based on random sampling from known Probability Density Functions (PDFs).

The second stage optimizes the BESS, PV and WT sizes within the modular approach, aiming at maximizing the NPV under each scenario set. This results in the determination of a total number l^* of solutions, but some of them can be non-unique, and by applying a minimum occurrence threshold it is possible to select only the l^{**} most frequent planning alternatives, with $l^{**} \le l^*$. Decisions regarding investments must be made at the beginning of the planning horizon, and operational costs are evaluated all over the planning horizon.

The third stage is therefore aimed at determining the best solution among the planning alternatives individuated in the second stage, based on three different criteria that are widely adopted in the relevant literature.

The three stages are described in detail in the following sub-Sections.

2.1. Markov-chain based methodology for long-term scenarios generation of uncertain variables

Scenarios of the uncertain variables involved in sustainable tunnel

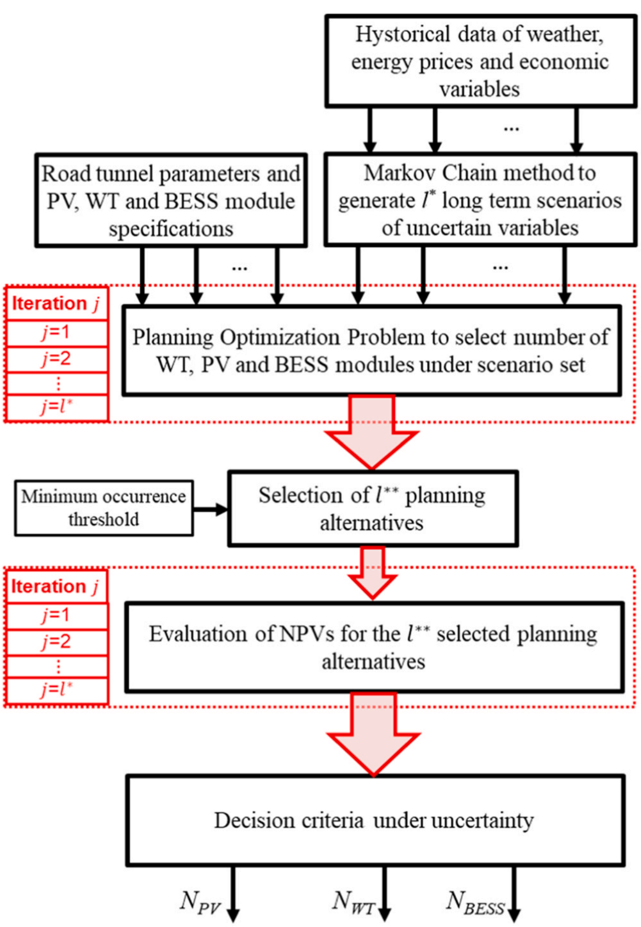

Fig. 2. Block scheme of the proposed optimal planning procedure.

planning that must be issued with a dense time resolution (i.e., one hour) are generated through an MC-based methodology. The methodology is presented below with reference to the generation of scenarios for the general uncertain variable x, that is assumed to take values in the N states $S^{\langle 1\rangle}, S^{\langle 2\rangle}, \ldots, S^{\langle N\rangle}$, and where each state corresponds to a bin of values. Exemplarily, if $l^{\langle j\rangle}, u^{\langle j\rangle}$ are the lower and upper bound of the generic j^{th} bin and $x_t \in [l^{\langle j\rangle}, u^{\langle j\rangle}[$, the variable is said to be at the j^{th} state $S^{\langle j\rangle}$ at time t, or equivalently $S_t = S^{\langle j\rangle}$.

2.1.1. Background: Discrete-time Markov Chain models

As well known, discrete-time MC models describe stochastic processes in which the probability of occurrence of each event depends only by the previous o states of the process [17,18]. The number o is the order of the MC process, and formally the independence property of a o-order MC is formulated as:

$$p(S_t|S_{t-k}, S_{t-2k}, \ldots, \ldots, S_1) = p(S_t|S_{t-k}, S_{t-2k}, \ldots, S_{t-ok}) \tag{1}$$

where k is the MC time step, that can be adequately selected either as $k = 1$ (consecutive states) or as $k > 1$ (periodical states), in the latter case on the basis of the seasonal properties of the variable time series.

Transitions among states are assessed in a frequentist manner by estimating the $\underbrace{N \times N \times \ldots \times N}_{(o+1)}$ transition tensor $\boldsymbol{A}$ that has its generic element $a_{i_1 i_2 \ldots i_o j}$ representing the probability of consecutive transitions among states $S^{\langle i_1\rangle} \to S^{\langle i_2\rangle} \to \ldots \to S^{\langle i_o\rangle} \to S^{\langle j\rangle}$. The element $a_{i_1 i_2 \ldots i_o j}$ can be estimated through the relationship:

$$a_{i_1 i_2 \ldots i_o j} = \frac{\#_{i_1 i_2 \ldots i_o j}}{\#_{i_1 i_2 \ldots i_o}} \tag{2}$$

where ${}_{i_1 i_2 \ldots i_o j}$ is the number of recorded times in which the variable x consecutively transited among states $S^{\langle i_1\rangle} \to S^{\langle i_2\rangle} \to \ldots \to S^{\langle i_o\rangle} \to S^{\langle j\rangle}$, and where ${}_{i_1 i_2 \ldots i_o}$ is the number of recorded times in which the variable x consecutively transited among states $S^{\langle i_1\rangle} \to S^{\langle i_2\rangle} \to \ldots \to S^{\langle i_o\rangle}$.

The MC can be used to predict the future state of the variable at time t in terms of probability of occurrence of future states $\pi_t^{\langle 1\rangle}, \pi_t^{\langle 2\rangle}, \ldots, \pi_t^{\langle N\rangle}$, where the generic j^{th} probability $\pi_t^{\langle j\rangle}$ is obtained from the probabilities of the previous o states as:

$$\pi_t^{\langle j\rangle} = \sum_{i_o=1}^{N} \sum_{i_{o-1}=1}^{N} \ldots \sum_{i_2=1}^{N} \sum_{i_1=1}^{N} \left(a_{i_1 i_2 \ldots i_o j} \bullet \pi_{t-ok}^{\langle i_1\rangle} \bullet \pi_{t-(o-1)k}^{\langle i_2\rangle} \bullet \ldots \bullet \pi_{t-2k}^{\langle i_{o-1}\rangle} \bullet \pi_{t-k}^{\langle i_o\rangle} \right) \tag{3}$$

Unitary and zero probabilities are considered when the data are observed or deterministically known (e.g., if the state $S^{\langle 3\rangle}$ is observed at time $t - 5k$, then $\pi_{t-5k}^{\langle 3\rangle} = 1$ and $\pi_{t-5k}^{\langle 1\rangle} = \pi_{t-5k}^{\langle 2\rangle} = \pi_{t-5k}^{\langle 4\rangle} = \ldots = \pi_{t-5k}^{\langle N\rangle} = 0$).

2.1.2. Two-stage MC-based methodology

The block scheme of the two-stage MC-based methodology used in this paper is illustrated in Fig. 3.

Input data of the target variable is initially divided into training and validation subsets. Training data is used to develop different MCs having different combinations of order o and number of states N, with their couples iterated in a grid search with $o \in [1, o^*]$ and $N \in [1, N^*]$, and where o^* and N^* are respectively the maximum considered order and the maximum considered number of states of the MCs.

The MC training particularly consists of estimating the related transition tensor $\boldsymbol{A}(o, N)$, which is then used to generate short-term forecasts $\widehat{x}_t(o, N)$ through the entire validation period (i.e., for any $t \in \Omega_{val}$, where Ω_{val} is the set of T_{val} time subscripts related to the validation period).

The accuracy of these short-term forecasts is assessed through a quantitative index, i.e., the Mean Absolute Error (MAE), calculated as it follows:

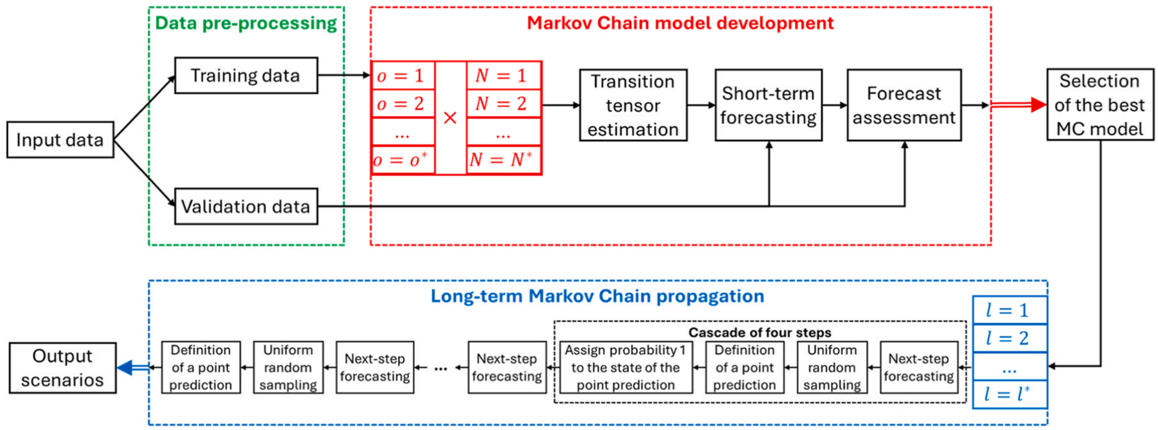

Fig. 3. Block scheme of the two-stage MC-based methodology.

$$MAE(o,N) = \frac{1}{T_{val}} \sum_{t\in\Omega_{val}} |\hat{x}_t(o,N) - x_t| \quad (4)$$

The best MC model is selected as the one with the smallest MAE, thus identifying the optimal order $\bar{o}$ and the optimal number of states $\bar{N}$. The corresponding best MC model is used in an iterative procedure that generates the required number $l^*$of scenarios for the optimal planning. In particular, for each generic l^{th} scenario generation, the optimal MC is propagated through the whole scenario length (i.e., all the hours for Y years) by performing a cascade of four steps at each $t \in \Omega_{test}$, where Ω_{test} is the set of time subscripts related to the test period:

i. next-step forecasting to predict probabilities $\pi_t^{\langle 1\rangle}, \pi_t^{\langle 2\rangle}, \ldots, \pi_t^{\langle \bar{N}\rangle}$;
ii. random sampling u from a uniform $U \sim [0,1]$ distribution;
iii. definition of a point prediction through the inverse sampling method, dropping u down the cumulated predicted probabilities, to identify the predicted state $\hat{S}_t$;
iv. assignment of probabilities to future, unobserved outcomes. Exemplarily, if $\hat{S}_t = S^{\langle j\rangle}$, then $\pi_t^{\langle j\rangle} = 1$, and $\pi_t^{\langle 1\rangle} = \ldots = \pi_t^{\langle j-1\rangle} = \pi_t^{\langle j+1\rangle} = \ldots = \pi_t^{\langle \bar{N}\rangle} = 0$. This step ensures that the MC can be applied at the next time index to perform the subsequent next-step forecasting.

2.2. Optimal planning model of modular DER system for sustainable road tunnel supply system

As mentioned before, the variables of the optimization problems are the integer numbers of modules N_{WT}, N_{PV} and N_{BESS} The planning optimization problem is aimed at maximizing the NPV, subject to various technical constraints that are discussed below. The assumptions made on the optimization problem are the following:

- the planning horizon of the economic analysis consists of Y years;
- the hourly road tunnel power profiles P_L is known by the road tunnel owner/manager through the whole planning horizon. In fact, this power profile is typically stable over the years.
- The road tunnel electrical network is modelled by a single-bus system, so the losses are neglected.

The inputs of the optimization problem are:

i. long term scenarios of variables requiring dense time resolution, i.e., wind speed w and solar radiation I_{rr} at the tunnel location, and the electrical energy selling price P_s in the related zonal market. As stated above, these scenarios are obtained from the MC-based methodology presented in sub-Section II.A;
ii. long-term scenarios of the yearly variation rate of energy purchase/sell cost α_{vr} [%] and of the discount rate α [%]. As stated above, these scenarios are obtained by random sampling from known PDFs, estimated or constructed from historical observations of these economic parameters;
iii. road tunnel parameters, assumed to be known by the road tunnel owner, that are: the energy tariff c_{en} [€/kWh], the maximum power $P_{PCC}^{\max}$ [kW] exchanged at the Point of Common Coupling (PCC), and the maximum surface $S_{\max}$ [m^2] available for the installation of WTs and PVs;
iv. characteristics of the single modules of WT, PV and BESS, that are fixed a priori and consist of:

- for WTs and PV, the nominal powers P_{WT}^n and P_{PV}^n [kW], the occupation surface S_{WT}^n and S_{PV}^n [m^2], the unitary installation costs C_{WT} and C_{PV} [€/kWp], and the PV efficiency η_{PV} [-];
- for BESSs, the capacity E_{Bess}^n [kWh], the nominal power P_{Bess}^n [kW], and the unitary installation cost C_{Bess} [€/kWh]. In addition, BESS is assumed to be made of lithium-ion batteries with a fixed maximum number N_c of charge/discharge cycles, and fixed minimum and maximum values SOC_{min} to SOC_{max} [%] of the State of Charge (SOC), either as suggested by the manufacturer or to comply with security/reliability requirements (e.g., for guaranteeing minimum levels of the SOC to possibly entirely supply the tunnel during unavailability of the upstream distribution network).

The BESS management strategy is fixed a priori and is based on the fact that the energy tariff of road tunnels is constant during the hours of the day. Considering this type of tariff, the following BESS strategy is applied: BESS involves charging during hours when the solar source should be available (for example, from 6 am to 7 pm) and discharging, if required, during the remaining hours. Obviously, the proposed procedure can be simply extended in the case of the application of other different BESS management strategies and/or in the presence of other energy tariff mechanisms.

As mentioned before, the objective function of the optimization problem is the NPV of investment. The NPV is a function of the annual cash flows that include annual costs and revenues taking into account the discount rate. In particular, the objective function includes: i) costs for the installation of the N_{WT}, N_{PV} and N_{BESS} modules, ii) costs paid to replace any equipment during the considered planning time horizon; and iii) management costs and operation costs sustained to supply the loads of road tunnel. The revenues derive from the energy sales on the market. Starting from these considerations, it is possible to define the overall objective function as:

$$NPV = \sum_{y=0}^{Y-1} \left[R(y) - C_{rep}(y) - C_{om}(y) \right] - C_{in}(0) \quad (5)$$

where $C_{in}(0)$ is the cost paid at year 0 to install the N_{WT}, N_{PV} and N_{BESS} modules, $C_{rep}(y)$ is the cost at year y beared to replace any equipment, and $C_{om}(y)$ includes the O&M costs at year y.

The installation cost $C_{in}(0)$ is:

$$C_{in}(0) = N_{WT} \quad C_{WT}P^n_{WT} + N_{PV} \quad C_{PV}P^n_{PV} + N_{Bess} \quad C_{Bess}E^n_{Bess} \tag{6}$$

The replacement cost $C_{rep}(y)$ is beared at the year of substitution $y_{rep} < Y$, and it is assumed mainly due to the replacement of the BESS systems (including batteries and inverters). Then, when (and if) the maximum number of charge/discharge cycles N_c is reached,[1] the BESS has to be replaced sustaining the following costs:

$$C_{rep}\left(y = y_{rep}\right) = C_{Bess}E^n_{Bess}\left(\frac{1}{1+\alpha/100}\right)^{y_{rep}} \tag{7}$$

The O&M cost $C_{om}(y)$ is the sum of the maintenance cost $C_m(y)$ and the operation costs $C_o(y)$. The maintenance cost $C_m(y)$ is calculated taking into account the maintenance cost of BESS $C_{m,BESS}(y)$ obtained, for each year, as a percentage of the BESS installation cost. The operation cost $C_o(y)$ is equal to the annual cost of purchased energy that depends on the strategy adopted for BESS charging and discharging modes. Here, assuming that H_{ch} and H_{dis} are the sets of charging and discharging hours, the strategy is the following: a) BESS is charged during H_{ch} h, up to $SOC_{\max}$, when the power from renewable sources (WT and/or PV) exceeds the load of the road tunnel P_L; b) BESS is discharged to supply the load of the road tunnel P_L during H_{dis} hours, only if SOC is greater than $SOC_{\min}$, and the power generated by renewable sources (WT and/or PV) is lower than the power of the load of the road tunnel. Note that usually, the hourly road tunnel power profiles include mainly the power required by tunnel lighting systems and ventilation systems and the lighting system is characterized by peak power in the morning [4].

Using this strategy, the power at PCC $P_{PCC}(y,h)$ in charging/discharging hours is:

$$P_{PCC}(y,h) = P_L(y,h) + \frac{P_{ch}(N_{Bess},y,h)}{\eta_{ch}} - P_{WT}[N_{WT},w(y,h)] - P_{PV}[N_{PV},I_{rr}(y,h)] \text{with} h \in H_{ch} \tag{8}$$

$$P_{PCC}(y,h) = P_L(y,h) - \quad \eta_{dis}P_{dis}(N_{Bess},y,h) - P_{WT}[N_{WT},w(y,h)] - P_{PV}[N_{PV},I_{rr}(y,h)] \text{with} h \in H_{dis} \tag{9}$$

and the operational cost $C_o(y)$ at year y is:

$$C_o(y) = \sum_{h \epsilon H_p} P_{PCC}(y,h)c_{en}(0,h) \quad \left(\frac{1+\alpha_{vr}/100}{1+\alpha/100}\right)^y \tag{10}$$

where:

- $P_{ch}(N_{Bess},y,h)$ and $P_{dis}(N_{Bess},y,h)$ indicate the charging and discharging powers of N_{BESS} BESS at year y and hour h;
- η_{ch} and η_{dis} are the BESS charging and discharging efficiencies;
- $P_{WT}[N_{WT},w(y,h)]$ and $P_{PV}[N_{PV},I_{rr}(y,h)]$ are the powers generated by the N_{WT} WTs at wind speed $w(y,h)$ and by the N_{PV} PVs at solar radiation $I_{rr}(y,h)$. Note that $P_{WT}[N_{WT},w(y,h)]$ is calculated starting from the wind speed $w(y,h)$ and the power curve of the selected WT provided by the manufacturer; $P_{PV}[N_{PV},I_{rr}(y,h)]$ can be simply calculated by applying the well-known linear relationship including irradiance I_{rr} and panel's surface and efficiency when the Maximum Power Point Tracking is used.
- H_p is the set of hours with positive $P_{PCC}(y,h)$ (purchasing hours);
- $c_{en}(0,h)$ is the unitary hourly energy tariff (at year 0 and hour h);

Note that: during charging hours $P_{ch}(N_{Bess},y,h)$ is zero if the renewable power by WT and/or PV is lower than the load power and during discharging hours $P_{dis}(N_{Bess},y,h)$ is zero if the renewable power by WT and/or PV is greater than the load power.

The hourly revenues derive from the energy sales on the market. In particular, during the discharging hours, if the power generated by WT, PV and BESS exceeds the load $P_L(y,h)$ of road tunnel, the exceeding power can be sold. Analogously, during the charging hours, the power generated by WT and PV exceeding the load and BESS charge can be sold. Then, the annual revenue $R(y)$ is obtained as:

$$R(y) = \sum_{h \epsilon H_s} |P_{PCC}(y,h)| P_s(y,h) \quad \left(\frac{1+\alpha_{vr}/100}{1+\alpha/100}\right)^y \tag{11}$$

where H_s is the set of hours with negative $P_{PCC}(y,h)$ (selling hours), and $P_s(y,h)$ is the energy selling price at year y and hour h.

It is here highlighted that, in eqs. from (5) to (11), the values of wind speed, solar radiation, price, annual variation rate and discount rates are known because they are generated as scenarios from the first stage, and all the other parameters are known except for the decision variables of the optimization problem N_{WT}, N_{PV} and N_{BESS}.

The constraints on the optimization problem include: i) the SOC of BESS must always be between $SOC_{\min}$ and $SOC_{\max}$; ii) the absolute value of the power exchanged at PCC must be less than $P^{\max}_{PCC}$; iii) the total occupied surface by WT and PV modules must be less than $S_{\max}$; iv) the number of BESSs is limited to a maximum value of N^*_{Bess} modules.

$$SOC(y,h-1) + \quad P_{ch}(N_{Bess},y,h) \le SOC_{\max} \text{with} \in H_{ch} \tag{12}$$

$$SOC(y,h-1) - \quad P_{dis}(N_{Bess},y,h) \ge SOC_{\min} \text{with} \in H_{dis} \tag{13}$$

$$|P_{PCC}(y,h)| \le P^{\max}_{PCC} \tag{14}$$

$$(N_{WT}S^n_{WT} + N_{PV}S^n_{PV}) \le \quad S_{\max} \tag{15}$$

$$N_{BESS} \le N^*_{Bess} \tag{16}$$

The formulated problem is a non-linear optimization problem with integer variables. These types of problems have been largely addressed in the relevant literature, and there are several algorithms that allow solving them (e.g., branch-and-bound, outer approximation, genetic and metaheuristic algorithms) [19]. Since the scope of our paper is not to develop a new algorithm for the solution of non-linear optimization problems with integer variables, it is here sufficient to use one of the consolidated algorithms from the available literature or implemented in academic and commercial optimization software. In this paper, we use a genetic algorithm [20] that is available, through the in-built function "ga", within the MATLAB's Global Optimization Toolbox [21].

2.3. Decision criteria under uncertainty

When decision problems are subject to uncertain inputs, several approaches can be applied to identify the best solution. This paper proposes a set of criteria, grounded in decision theory, to select alternatives that demonstrate superior performance across the considered scenarios. To apply these criteria, a framing of the decision problem is mandatory. The decision maker handles a number of planning alternatives (referred to as $PA_1, PA_2, \ldots, PA_{l^{**}}$, where l^{**} is the number of planning options) that have different outcomes in the considered scenarios (referred to as $SC_1, SC_2, \ldots, SC_{l^*}$, where l^* is the number of considered scenarios). In the framework of the problem under consideration, the l^{**} alternatives are selected as the most frequent solutions of the optimization problem, described in sub-Section II.B, and are expressed in terms of numbers of BESS, PV and WT modules; the l^* scenarios characterize

[1] A charge/discharge cycle of a BESS is counted when the available capacity of the BESS is fully used to supply the load of the road tunnel.

the behaviour of random variables of interest as explained in sub-Section II.A.

For each planning alternative PA_i ($i = 1,\ldots,l^{**}$), the NPV has to be evaluated in each scenario SC_j ($j = 1,\ldots,l^{*}$), returning the corresponding NPV_{ij}; to do that, the methodology described in sub-Section II.B and the model expressed by Eqs. (5)-(11) have to be applied. These outcomes of the planning alternatives in all the scenarios constitute the decision matrix. In this paper, the NPV is chosen as the metric to evaluate the decisions; of course, further metrics could be used.

After having built the decision matrix, the decision maker has to select the best planning alternatives. This can be done by applying several criteria. In this paper, three criteria are considered, and they are presented below.

i) Criterion 1: criterion of the maximization of the average NPV

The first considered criterion is aimed at the maximization of the average NPV [22]. For each planning alternative PA_i ($i = 1,\ldots,l^{**}$), the $NPV_{mean}(PA_i)$ is computed by taking the mean of the values $NPV(PA_i, SC_j)$, with $j = 1,\ldots,l^{*}$, associated then with all the l^{*} scenarios:

$$NPV_{mean}(PA_i) = \frac{\sum_{j=1}^{l^*} NPV(PA_i, SC_j)}{l^*} \quad (17)$$

The optimal alternative $PA_{opt}^{\langle crit_1\rangle}$ found with the application of this first criterion is identified as the one exhibiting the highest average NPV (17):

$$PA_{opt}^{\langle crit_1\rangle} = \arg\max_{i=1,\ldots,l^{**}} NPV_{mean}(PA_i) \quad (18)$$

By applying this criterion, planning alternatives that perform optimally on average across all future scenarios are individuated. However, this approach may lead to significant regret if the scenario actually occurring deviates substantially from the average.

It is worth noting that this criterion is known as the expected value maximization; if each scenario is characterized by a probability of occurrence, reference to the expected value has to be made; in this case, by applying (17), the equal likelihood of the scenarios has been assumed.

ii) Criterion 2: maximax (optimistic) criterion

The second optimist criterion involves selecting the alternative that yields the highest possible value of the NPV across all scenarios [23]. First, for each alternative $i = 1,\ldots,l^{**}$, the maximum value $NPV_{\max}$ of the NPV is individuated:

$$NPV_{\max}(PA_i) = \max_{j=1,\ldots,l^*} NPV(PA_i, SC_j) \quad (19)$$

Then, the optimal alternative $PA_{opt}^{\langle crit_2\rangle}$ found with the application of this second criterion is individuated as the alternative associated with the maximum value of (19), as:

$$PA_{opt}^{\langle crit_2\rangle} = \arg\max_{i=1,\ldots,l^{**}} NPV_{\max}(PA_i) \quad (20)$$

This criterion assumes an optimistic approach that is based on selecting the best possible outcome for each alternative.

iii) Criterion 3: minimax regret criterion

The third criterion is based on the minimization of the maximum regret [22]. Regret can be quantified as the difference between the optimal outcome and the actual outcome for a given scenario. For each scenario SC_j with $j = 1, \ldots, l^*$, first, the optimal NPV outcome can be easily computed as:

$$NPV_{opt}(SC_j) = \max_{i=1,\ldots,l^{**}} NPV(PA_i, SC_j) \quad (21)$$

Then, the regret $R(PA_i, SC_j)$ incurred when selecting the planning alternative PA_i when the scenario SC_j actually occurs is determined as:

$$R(PA_i, SC_j) = NPV_{opt}(SC_j) - NPV(PA_i, SC_j) \quad (22)$$

and, for each alternative, the maximum regret can be identified as:

$$R_{\max}(PA_i) = \max_{j=1,\ldots,l^*} R(PA_i, SC_j) \quad (23)$$

Finally, the optimal alternative $PA_{opt}^{\langle crit_3\rangle}$ found with the application of this third criterion is individuated as the alternative associated with the minimum value of (23), i.e.:

$$PA_{opt}^{\langle crit_3\rangle} = \arg\min_{i=1,\ldots,l^{**}} R_{\max}(PA_i) \quad (24)$$

This criterion assumes a conservative approach trying to minimize the maximum potential loss or regret and is particularly advantageous for risk-averse decision-makers who would like to minimize the occurrence of negative outcomes.

3. Numerical applications on real-world tunnels

The case studies presented in this Section refer to a specific application; however, the proposed optimal planning procedure is not limited to the case of APROTs. The three stages of the procedure can be easily adapted for application in different contexts.

Several numerical experiments obtained applying the optimal planning procedure to road tunnels in different regions of Italy have been carried out to validate the proposed approach. In this Section, the results of two case studies are reported with reference to two actual road tunnels in Italy to evaluate the impact of the different load profiles of tunnels, the different availabilities of renewable primary energy sources and the different energy prices. Note that the two tunnels are located in two different Italian bidding areas, therefore zonal prices are different in the two considered case studies.

In both case studies the planning horizon of the economic analysis is $Y = 20$ years. The WT and PV single module specifications are: $P_{WT}^{n} = 10$ kW, $P_{PV}^{n} = 10$ kWp ($\eta_{PV} = 0.17$) with dimensions $S_{WT}^{n} = 100$ m^2 and $S_{PV}^{n} = 58$ m^2, and unitary costs $C_{WT} = 1630$ €/kW and $C_{PV} = 1000$ €/kWp [24,25].

The BESS module specifications are: $E_{Bess}^{n} = 12.5$ kWh, $P_{Bess}^{n} = 2.5$ kW, $C_{Bess} = 180$ €/kWh and $\eta_{ch} = \eta_{dis} = 0.97$. In addition, we consider BESSs with lithium-ion batteries having a number $N_c = 3800$ of charge/discharge cycles, and with $SOC_{\min} = 10$ % and $SOC_{\max} = 100$ % [25].

With reference to the uncertain input data, the results of the first stage of the proposed optimal planning procedure are described in dedicated Sub-sections for each case study and provide $l^* = 2000$ generated scenarios for the variables that have hourly variation (solar irradiance, wind speed, and prices). The PDFs from which we instead picked the $l^* = 2000$ scenarios of the variables that vary once per year (i.e., variation rates α_{vr} and discount rate α) are uniform distributions U $\sim [-1, 2]$ and U $\sim [1, 4]$, respectively, as they appear to represent well the historical observations of these economic parameters.

The results obtained by applying the optimal sizing maximizing NPV under the scenario set and the final decisions regarding investments are reported in the following sub-Sections.

3.1. Case study 1

The road tunnel parameters are: the energy tariff $c_{en} = 0.2$ €/kWh; the maximum power exchanged at PCC, $P_{PCC}^{\max} = 400$ kW; and the maximum available surface $S_{\max} = 2250$ m^2. Fig. 4 exemplarily shows load power of road tunnel, in pu of the maximum value, during a winter week and a summer week.

3.1.1. MC-based long term scenarios

Long-term scenarios of wind speed, solar radiation, and energy prices are obtained through the MC-based procedure, applied independently for each hour of the day, using actual data collected from the European Centre for Medium-range Weather Forecasts (ECMWF) [26] and from the Transparency Platform of ENTSO-e [27] from 2016 to 2019. Data are split into a three-years (2016–2018) training set and into a one-year

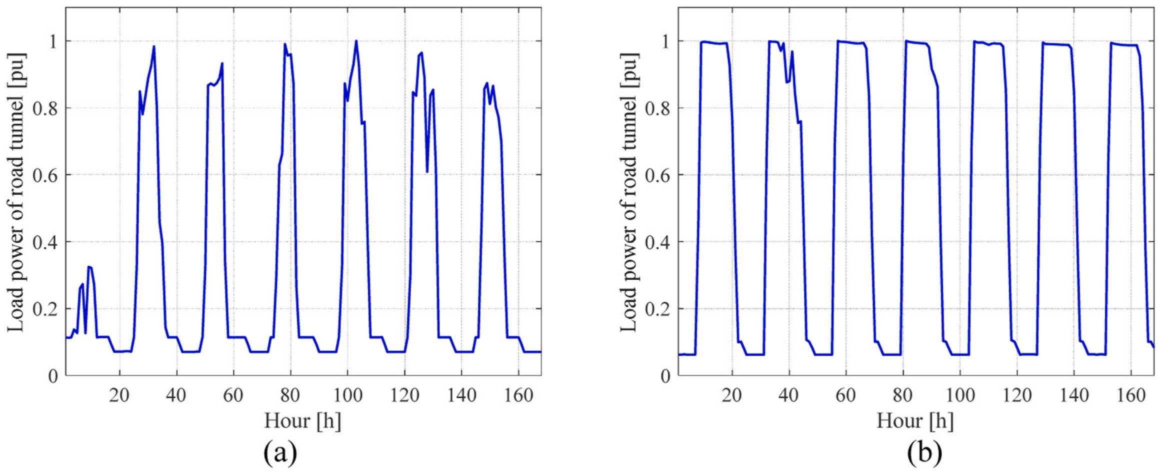

Fig. 4. Case study 1. Load power of roar tunnel in pu during (a) a winter week and (b) a summer week.

(2019) validation set, for MC development purposes. The optimal order and number of states of the MCs are searched by setting $o^* = 2$ and $N^* = 100$ (for the grid search of the number of states, incremental steps of five states are considered).

Table I summarizes the results of the optimal MC selection, in terms of optimal order and number of states, for each hour of the day. Missing values in the solar radiation columns of Table I indicate that the MC model is not developed for those nighttime hours, as the solar irradiance is deterministically zero. Fig. 5 exemplarily shows the first three scenarios during a summer week and a winter week in the first year. Fig. 6 exemplarily shows instead the Quantile-Quantile (Q-Q) plots [28] of several generated scenarios of hourly solar irradiance (Figs. 6a-6c) and of hourly wind speed (Figs. 6d-6f) against their empirical observations. Q-Q plots appear to empirically be close to the ideal behavior (i.e., a straight line at 45° degree), denoting a good resemblance of the generated scenarios with respect to the empirical data.

3.1.2. Results of the planning procedure

The second stage of the procedure optimizes BESS, PV and WT sizing maximizing the NPV under the scenario set, determining the planning alternatives. The results are l^* optimized solutions that include l^* vectors N_{WT}, N_{PV} and N_{BESS} with corresponding annual cash flows and NPVs. Among them, it is possible to identify and count the unique solutions that recur. Fig. 7 illustrates a bar diagram with the number of occurrences for each unique solution. The results show that the number of unique solutions is 90 and that there are some optimal sizes maximizing NPV that repeat multiple times in several scenarios.

Assuming a threshold of 85 occurrences, $l^{**} = 6$ planning alternatives are selected and the third stage to determine which is the best solution to be enforced. In particular, the decision matrix $l^{**} \times l^* = 6 \times 2000$ is calculated, and in Table II we report the optimal values of the N_{WT}, N_{PV} and N_{BESS}, and the maximum, and mean NPVs, and the maximum regret related to the six most frequent solutions. From the results in Table II it can be observed that for this road tunnel:

- in the considered geographical site the solar source guarantees more profit than the wind source, in fact usually $N_{WT} = 0$;
- applying the criterion of the maximization of the average NPV and the maximax criterion the best solution, evidenced in bold in

Table I
Case study 1: optimal orders and numbers of states of Markov Chains.

Hour of the day [h]	Solar radiation		Wind speed		Price	
	Optimal order $\bar{o}$	Optimal number of states $\bar{N}$	Optimal order $\bar{o}$	Optimal number of states $\bar{N}$	Optimal order $\bar{o}$	Optimal number of states $\bar{N}$
1			2	35	1	10
2			2	25	2	25
3			2	35	2	65
4			2	40	2	65
5			2	40	2	85
6	2	90	2	60	1	20
7	2	25	2	30	2	35
8	2	50	2	25	2	45
9	2	25	2	20	1	15
10	1	20	2	45	1	15
11	2	40	2	15	2	40
12	1	20	1	15	2	85
13	1	40	2	40	2	50
14	1	20	2	30	2	40
15	2	15	2	30	2	50
16	1	15	2	35	2	20
17	1	35	2	15	2	15
18	1	75	1	15	2	50
19	2	45	2	15	2	25
20	2	50	2	25	2	70
21			2	30	1	15
22			2	55	2	60
23			2	30	1	35
24			2	40	1	25

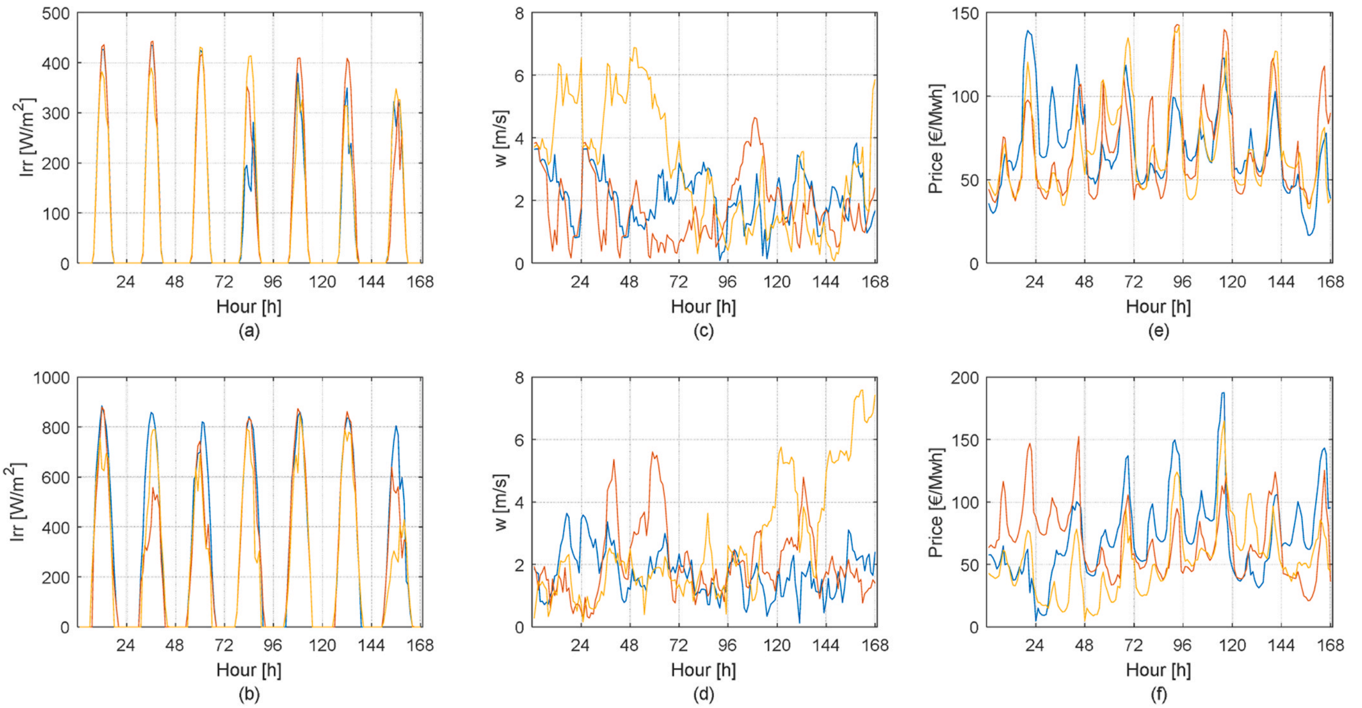

Fig. 5. Case study 1. Example of scenarios of: solar irradiance (a), wind speed (c), and prices (e) during a winter week; solar irradiance (b), wind speed (d), and prices (f) during a summer week.

Table II, is PA_1. Using the minimax regret criterion the best solution is PA_4;

- the optimal number of BESSs does not reach the maximum possible value while the optimal number of PVs leads to occupying a surface near to $S_{\max}$.

Eventually, the boxplot of the annual cash flow of the best solution (planning alternative PA_1) and the cash flow of the road tunnel without DERs (red line) are reported in Fig. 8. The use of the MG with DERs allows us to obtain a positive NPV and a payback time return of about 9 years. The dispersion of cash flows shown by box plots increases with the years. This is due to the increasing impact of the exponential factor rising with y.

3.2. Case study 2

The road tunnel parameters are: the energy tariff is $c_{en} = 0.2$ €/kWh; the maximum power exchanged at PCC $P_{PCC}^{\max} = 300$ kW; and the maximum available surface $S_{\max} = 2200$ m^2. Fig. 9 exemplarily shows load power of road tunnel, in pu of the maximum value, during a winter week and a summer week.

3.2.1. MC-based long term scenarios

Long-term scenarios of wind speed, solar radiation, and energy prices are obtained through the MC-based procedure, applied independently for each hour of the day, using actual data collected from the ECMWF and from the ENTSO-e from 2016 to 2019. Data are split into a three-years (2016–2018) training set and into a one-year (2019) validation set, for MC development purposes. The optimal order and number of states of the MCs are searched by setting $o^* = 2$ and $N^* = 100$ (for the grid search of the number of states, incremental steps of five states are considered).

Table III summarizes the results of the optimal MC selection, in terms of optimal order and number of states, for each hour of the day. Missing values in the solar radiation columns of Table III indicate that the MC model is not developed for those nighttime hours, as the solar irradiance is deterministically zero. Fig. 10 exemplarily shows the first three scenarios during a summer week and a winter week in the first year.

3.2.2. Results of the Planning Procedure

The results of the second stage of the procedure are l^* optimized solutions that include l^* vectors N_{WT}, N_{PV} and N_{BESS} with corresponding annual cash flows and NPVs. Among them, it is possible to identify and count the unique solutions that recur. Fig. 11 illustrates a bar diagram with the number of occurrences for each unique solution. The results show that the number of unique solutions is 54 and that there are some optimal sizes maximizing NPV that are repeated in several scenarios.

Assuming a threshold of 130 occurrences, $l^{**} = 6$ planning alternatives are selected and the third stage to determine which is the best solution to be enforced. In particular, the decision matrix $l^{**} \times l^* = 6 \times 2000$ is calculated, and in Table IV we report the optimal values of the N_{WT}, N_{PV} and N_{BESS}, and the maximum, and mean NPVs, and the maximum regret related to the six most frequent solutions. From the results in Table IV it can be observed that for this road tunnel:

- in the considered geographical site both solar and wind sources guarantee profit. In this road tunnel site, the wind speed is higher while the irradiance is usually lower than in Case Study 1.
- the NPV is lower than Case study 1 since the difference between peak and off-peak hours of the load power in the tunnel of Case study 2 is reduced. This leads to a significant reduction of selling energy and an increase of the one purchased during the off peak hours.
- Applying the criterion of the maximization of the average NPV, the maximax criterion and the minimax regret criterion the best solution, evidenced in bold in Table IV, is PA_2.

Eventually, in Fig. 12 the boxplot of the annual cash flow of the best solution and the cash flow of the road tunnel without DERs are reported. The use of the MG that includes renewable generators and storage systems allows to obtain a positive NPV and a payback time return of about 15 years.

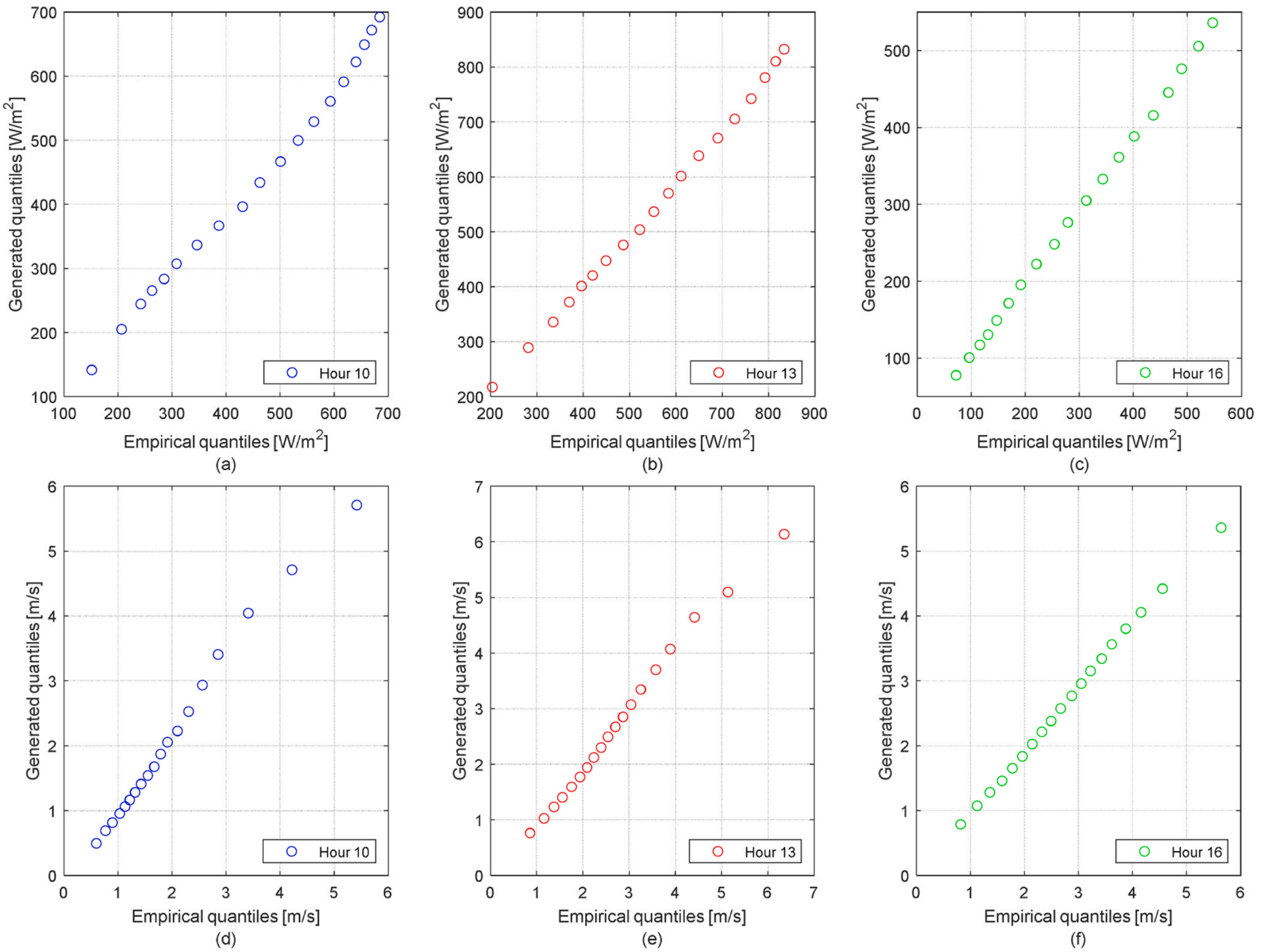

Fig. 6. Case study 1. Q-Q plots of solar irradiance generated scenarios at hour 10 (a), 13 (b) and 16 (c) of the day against their empirical observations; Q-Q plots of wind speed generated scenarios at hour 10 (d), 13 (e) and 16 (f) of the day against their empirical observations.

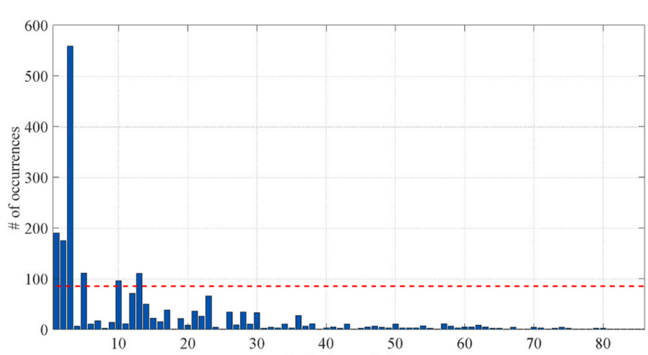

Fig. 7. Case study 1: Number of occurrences of unique solutions and threshold (red dashed line).

Table II
Case study 1: N_{WT}, N_{PV}, N_{BESS}, mean, max NPV and maximum regret of the most frequent solutions.

Planning alternatives	N_{WT}	N_{PV}	N_{Bess}	NPV$_{mean}$ [k€]	NPV$_{max}$ [k€]	R$_{max}$ [k€]
PA_1	0	37	8	**573.42**	**893.89**	15.09
PA_2	0	36	8	562.41	876.43	30.75
PA_3	0	37	7	565.55	879.92	28.33
PA_4	0	38	8	566.43	892.67	**12.12**
PA_5	0	38	9	555.86	884.98	29.55
PA_6	1	36	8	552.81	860.83	40.38

4. Conclusions

The problem of road tunnel energy consumption and sustainability is considered in this paper, with the specific aim to perform the optimal planning of an MG that includes renewable generators and storage systems to supply the tunnel loads. A new optimal procedure is proposed to determine the number of modules of DER units that maximize the NPV through the investment lifetime and, thus, to assess the profitability of the MG investment. The proposed methodology incorporates all planning uncertainties, includes an advanced MC-based methodology for the long-term generation of stochastic variable profiles, and satisfies the technical and contractual constraints selectable by the tunnel owner. Moreover, the decision criteria that are most frequently proposed in the literature for the selection of the optimal solution are considered to finalize the decision making process.

The proposed procedure is applied in several case studies of actual road tunnels to verify the benefits, the flexibility and the effectiveness of the proposed approach. The results of two case studies are reported with reference to road tunnels in the South Italian bidding areas, to evaluate the impact of different profiles of tunnel loads, different availabilities of renewable primary energy sources and the different zonal energy prices.

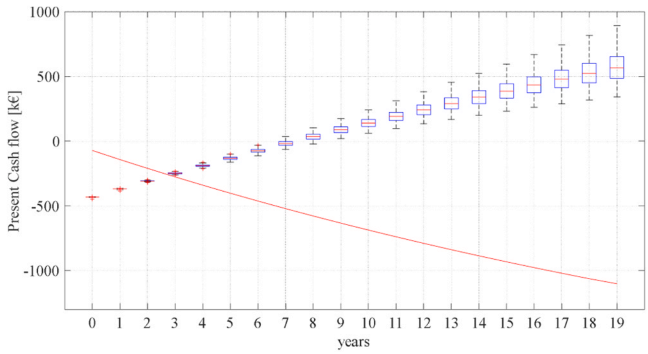

Fig. 8. Case study 1: boxplot of annual cash flow of the best solution PA_1 with MG that includes renewable generators and storage systems and cash flow (red line) of road tunnel without DERs.

The use of an MG that includes renewable generators and storage systems always allows to obtain a positive expected NPV and a payback return time that is about 9 years and 15 years, respectively.

Although the numerical applications refer to the specific case of APROTs, the proposed optimal planning procedure can be applied to various planning problems that include long-term planning and uncertainty factors/variables. In fact, the three stages of the procedure are general and can be customized according to the specific case study.

Ongoing activities to enhance the proposal are focused on: i) the extension of the proposed approach to two or more road tunnels connected to the same electrical primary substation to implement the concept of self-consumption and energy communities and to enable a better utilization of primary renewable energy sources; ii) the integration of external loads to the tunnel, such as charging stations, with the consequent possible necessity of tools for the forecasting of the external loads; iii) the application in case of real-time tariffs of energy and iv) different management strategies (for example, improving lifetime of BESS),and other services (e.g., flexibility resources, enhancement of security and reliability of the tunnel supply) that can be provided by

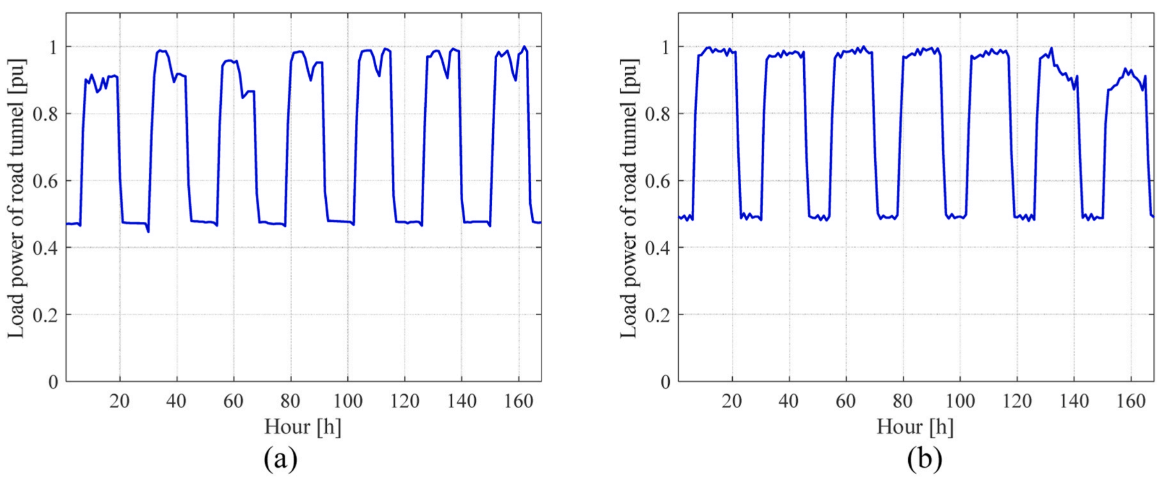

Fig. 9. Case study 2. Load power of road tunnel in pu during (a) a winter week and (b) a summer week.

Table III
Case study 2: optimal orders and numbers of states of Markov Chains.

Hour of the day [h]	Solar radiation		Wind speed		Price	
	Optimal order $\bar{o}$	Optimal number of states $\overline{N}$	Optimal order $\bar{o}$	Optimal number of states $\overline{N}$	Optimal order $\bar{o}$	Optimal number of states $\overline{N}$
1			2	35	1	75
2			2	45	1	65
3			2	40	2	35
4			2	40	2	85
5	2	85	2	30	2	35
6	2	55	2	40	2	80
7	1	25	2	50	2	75
8	2	35	2	45	2	30
9	1	60	2	55	1	30
10	1	35	2	60	1	40
11	1	30	2	25	2	95
12	1	40	1	30	2	50
13	1	35	2	45	1	55
14	1	45	2	45	1	70
15	1	35	2	50	2	65
16	1	20	2	30	2	30
17	1	25	2	30	1	30
18	2	45	2	50	1	75
19	2	60	2	40	1	75
20	2	25	2	65	1	25
21			2	50	1	80
22			2	55	1	10
23			2	30	1	75
24			1	30	2	10

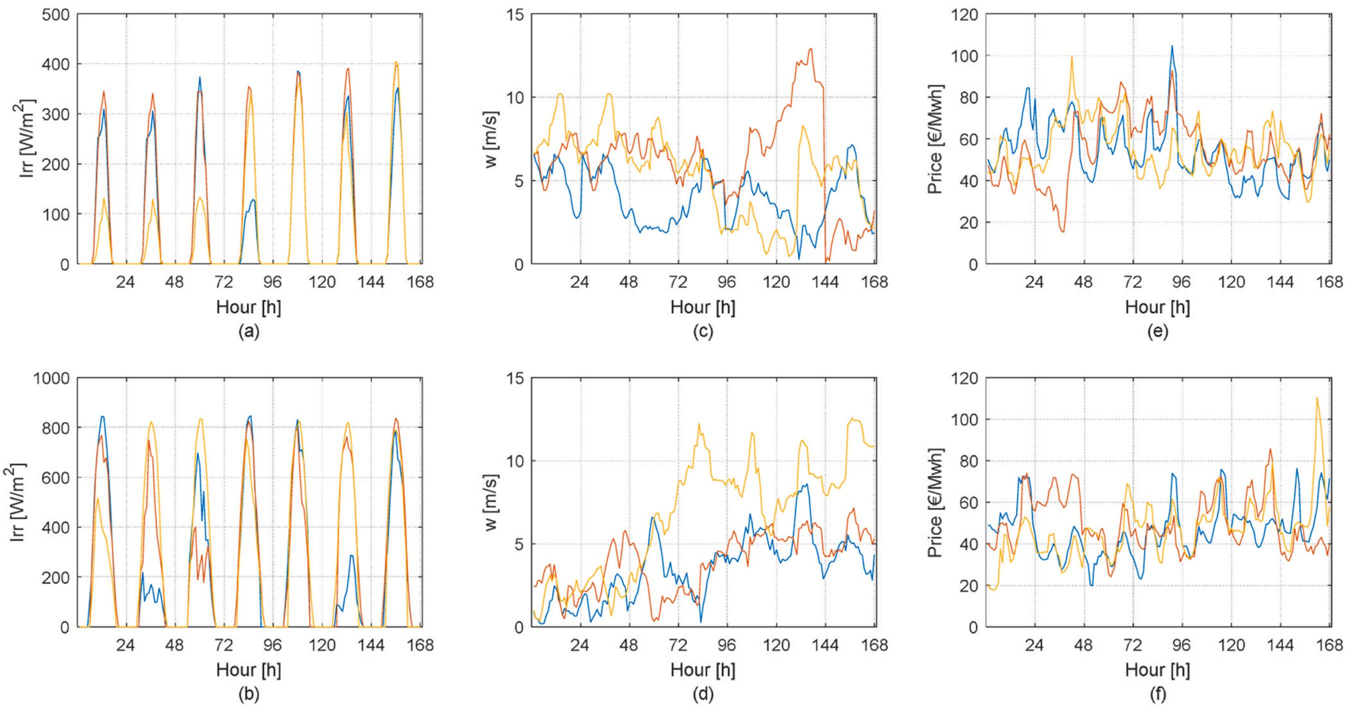

Fig. 10. Case study 2. Example of scenarios of: solar irradiance (a), wind speed (c), and prices (e) during a winter week; solar irradiance (b), wind speed (d), and prices (f) during a summer week.

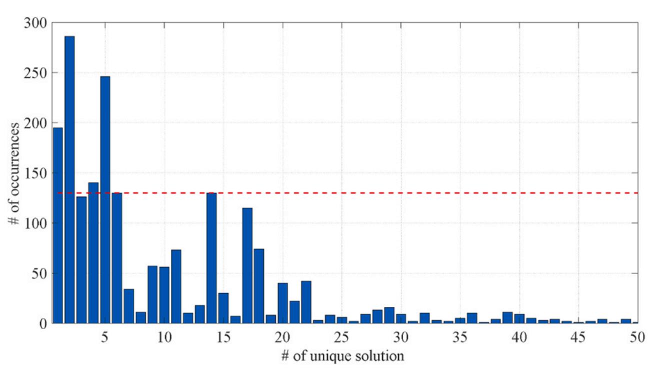

Fig. 11. Case study 2: Number of occurrences of unique solutions.

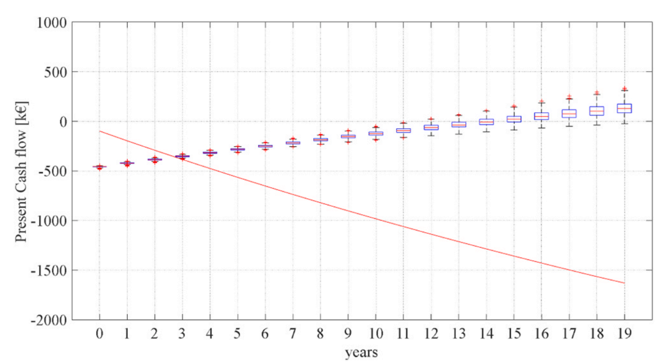

Fig. 12. Case study 2: boxplot of annual cash flow of the best solution with MG that includes renewable generators and storage systems and cash flow (red line) of road tunnel without DERs.

Table IV
Case Study 2: N_{WT}, N_{PV}, N_{BESS}, Mean, Max NPV and Maximum Regret of the Most Frequent Solutions.

Planning alternatives	N_{WT}	N_{PV}	N_{Bess}	NPV_{mean} [k€]	NPV_{max} [k€]	R_{max} [k€]
PA_1	8	24	9	106.03	290.63	56.59
PA_2	10	21	10	**138.36**	**347.22**	**17.15**
PA_3	10	21	9	131.13	334.72	30.44
PA_4	11	19	10	129.44	336.48	16.02
PA_5	10	21	8	123.02	322.31	40.85
PA_6	8	24	10	118.16	303.92	44.69

BESSs.

CRediT authorship contribution statement

D'Ambrosio Stefano: Writing – review & editing, Supervision, Data curation. **Sebastiano Nicotra:** Data curation, Writing – review & editing, Supervision. **Enrico Carpaneto:** Writing – review & editing, Conceptualization, Methodology. **Pierluigi Caramia:** Writing – review & editing, Supervision, Conceptualization, Writing – original draft, Methodology. **Antonio Bracale:** Writing – review & editing, Supervision, Conceptualization, Writing – original draft, Methodology, Software. **Angela Russo:** Conceptualization, Writing – original draft, Supervision, Writing – review & editing, Methodology. **Pasquale De Falco:** Methodology, Writing – review & editing, Software, Writing – original draft, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors declare that they didn't use Generative AI and AI-assisted technologies in the writing process'.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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