A user-mode distributed energy management architecture for smart grid applications

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A B S T R A C T

Future smart grids will require a flexible, observable, and controllable network architecture for reliable and efficient energy delivery under uncertain conditions. They will also necessitate variability in distributed energy generators and demand-side loads. This study presents a tree-like user-mode network architecture responding to these requirements. The approaches presented for the next-generation grid architecture facilitate the management of distributed generation strategies based on renewable sources, distributed storage, and demand-side load management.

The authors draw a framework for the future digital power grid concept and assess its viability in relation to volatile, diverse generation and consumption possibilities. In this sense, probabilistic energy balance analyses of tree-like user-mode networks with a stochastic end-user population are conducted to investigate the energy reliability of the proposed grid. A case study based on published generation and consumption profile data is also presented, and several generation scenarios formed by variants of this data are discussed.

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1. Introduction

The complexity of the electric power infrastructure continues to grow with increasing load demand [1]. In order to respond to this in an environmentally friendly manner, the integration of distributed renewable energy farms and the utilization of distributed energy storage are becoming major concerns for stakeholders involved in the design of future energy delivery grids. The conventional electric grid model, known as the dump grid, is not versatile enough to properly respond to these expectations [2]. This is because in traditional grids, the power flow is mainly designed to be unidirectional, supporting a continuous flow from power stations to static consumers. In future grids, static consumers will not be desirable; rather, users will be active, and therefore the power flow in grids need to be capable of dynamically switching between the consumer and local renewable energy providers.

This switching in the function of consumers requires a smarter grid infrastructure in order to deal with the dynamic alterations in power flows throughout the network. Unfortunately, the instantaneous flow control and optimization operations are a challenging task for the traditional electric power grid because of the difficulty in obtaining an accurate system representation in real-time [1]. There is therefore a need for more observable, accessible, and controllable network infrastructures. Future grids, also referred to as smart grids, will include distributed volatile renewable energy sources, domestic energy storage, and uncertain load demands due to the diversity of appliances. The smart grid will have to intelligently and automatically perform control and optimization operations and manage the rapid dynamic reconfiguration of system parameters to handle such distributed and volatile energy and load dispatches [3,4].

Due to increasing energy prices and the greenhouse effect, more efficient electricity production is desirable, preferably based on renewable resources. One of the most striking technologies involves generation methods using such resources, as evident in wind turbine and photovoltaic (PV) parks [4–7]. The use of these technologies, particularly at the domestic level, will greatly reduce energy losses in transport and hence the cost of energy. The applicability of these technologies depends on three main concepts related to future energy delivery and sharing grids: distributed generation (DG), distributed energy storage (DES), and demand-side load management (DSL).

In DG, energy sources are distributed into the power grid, ranging from the megawatt level to domestic generators at the kilowatt level such as renewable sources, micro-turbines and...
combined heat and power plants (CHP) [4–17]. In future smart grids, domestic energy generation will play a substantial role in renewable energy generation and energy efficiency [8]. Local energy production, storage, and consumption will greatly reduce transportation loss and complications in global maintenance management, and therefore the cost of energy. In this sense, DG will be the fundamental element of microgrids [14–17], in which energy production, storage, and consumption can be locally carried out in an islanded manner. Future microgrids are expected to operate as a self-supporting energy system (islanded operation), importing only a small amount of electricity from outside of the cluster [4,16], or even exporting their redundant energy production to neighboring clusters.

Energy storage is a key underpinning of the concept of the smart grid, which aims to support sustainable energy provision [18]. Particularly with the growing amount of renewable resources in the electricity supply chain, there is a growing demand for electricity storage [4]. However, large-capacity electricity storage is difficult to implement and leads to high losses; DES implementation is a possible solution to the problem of the energy storage requirements of the smart grid. Another advantage of DES implementation in a smart grid is that micro-storage (or domestic storage) supports DSLM strategies [19], increasing generation efficiency by enabling peak demand shaving that uses stored energy [14,15]. Domestic energy storage controlled by an intelligent management system can serve to shift the electricity demand away from peak periods. The management of peak demand via intelligent management techniques [18] will make the grid smarter and more energy efficient [19].

Recent efforts of diverse stakeholders to realize smart grids have exhibited the following prioritized trends: reliability, renewable resources, demand-side response, electric storage, and electric transportation [20]. However, a common vision of stakeholders in terms of the interaction of appliances and the management policy of grid resources is needed to facilitate the integration of the evolving smart grid resources.

This paper presents a probabilistic analysis of a reliable, controllable, demand-responsive, balanced energy delivery network architecture for the decentralized hierarchical integration of microgrids; further, this promotes prevailing DG, DES, and DSLM concepts. The grid architecture is defined via appliance interaction and interconnection models. This study focuses on the presentation of a feasible model for the integration and management of evolving smart-grid appliances that is responsive to stakeholders’ future grid expectations such as energy reliability, the use of diverse renewable energy resources [21], demand-responsive intelligent management [22,23], and energy-efficient transportation. The decentralized hierarchical architecture of the energy delivery network provides a scalable and flexible interaction between smart grid participants [24–27]. Advantages of decentralized hierarchical architectures were discussed on large-scale distributed systems in data processing [28], distributed control [29,30] and power distribution [24,26]. Future smart grids should be scalable and flexible structure so as to rapidly respond demands of active users, called as prosumers. The traditional, one-way, centralized network architectures are not effective to respond volatile, diverse generation and consumption profiles of active users. In a previous work, a prosumer-based, service-oriented architecture were discussed and remarked that prosumer-based decentralized architectures can serve as platform for the development of a large number of innovative smart grid applications [31]. Katz et al. discussed an information-centric energy infrastructure for the 21st century and they suggested that pervasive information would allow us to use energy more effectively, by agilely dispatching it to where it is needed, integrating intermittent renewable sources and intelligently adapting loads to match the available energy [26].

Energy balance is a main objective when it comes to developing reliable energy grids that exhibit uncertainty and variation in both energy generation [32] and the demand profiles of appliances. The real-time decentralized control of energy flows is necessary to maintain energy balance over the entire network. Reliability and efficiency in energy distribution can be achieved by smartly controlling the flow of energy throughout the network. The modeling of an electrical system that considers the stochastic process and probabilistic factors (social, ecological, physical,
Fig. 1. (a) Appliance scheme of a fully functional end-user model. (b) Electrical equivalent circuit of a dynamic end-user for energy transport. (c) A dynamic end user representation in energy flow schema.
connected to the nodes convey the energy bidirectionally. In the conventional grid, energy normally flows one-way, continuously from the top down. Power stations accommodate the top of the distribution hierarchy of the grid and supply the consumer, who is at the bottom of the distribution hierarchy. In the UMN architecture, all generators and consumers are placed at the bottom of a tree-like node hierarchy as end users. Energy flows are controlled by the nodes in both directions, from the bottom up for energy export and from the top down for energy import.

Nodes in the lowest rank are called first-order nodes and are denoted by mart grid in Fig. 2. These nodes are directly connected to end users and conceptually implement the microgrid concept in that they integrate all end-user appliances beneath the node domain. A first-order node exports redundant energy from its own domain in ES mode or imports the required energy into its own domain in EC mode. Such nodes do not only function as a bridge of energy flows between the end-user cluster and grid nodes, but also administer end-user activity on the node domain as a domain master for end users. As a slave, every end user has to obey the commands of the first-order node. As a master, a first-order node is responsible for providing line synchronization signals [38], monitoring transient stability problems, dealing with reliability, security, and maintenance issues, declaring energy costs in the domain, etc.

First-order nodes are connected with each other via second-order nodes. Second-order nodes manage the energy flow among first-order nodes, and thus provide a regional integration of microgrids. A second-order node is also master of the first-order node cluster, and is authenticated to perform all line management operations in its own domain. The global integration of microgrids can be achieved by third-order or higher-order nodes in this manner. Third-order nodes directly interconnect second-order nodes and manage the energy flow and energy balance between second-order nodes. From this point of view, higher-order nodes allow smart-grid integration in a larger geographical area in the manner of a standardized and domain-wise expansion approach. At this point, the problem can be reduced to implementing node-management strategies for a reliable, balanced, efficient energy-sharing policy.

2.2. Energy-balanced management of a user-mode network model

The two main objectives of energy-balanced management of a UMN are summarized as follows:

i) Energy reliability: In this study, the energy reliability of a network refers to the assurance of an uninterrupted energy distribution to all consumer elements. The energy demand and generation of a practical network are supposed to fluctuate instantaneously and spatially, and this makes the energy reliability issue the first priority of network management. A UMN has to ensure uninterrupted energy delivery to all end users over a specific time period. This is called the energy assurance period (EAP), and is denoted by $T_E$.

ii) Energy efficiency: After accomplishing the goal of energy reliability with an acceptable EAP, the second priority of the UMN will be energy efficiency, which is achieved by generation from renewable sources and the self-supporting operation of the grid (the islanded operation of microgrids [4,16]). The self-supporting approach is based on the local generation and consumption of energy, where the cost of energy is reduced by decreasing losses in energy transport and the costs of maintenance and management operations for the sake of the localized service.

Energy balance is a main concern for the reliable and efficient delivery of energy over a network; all complex systems in nature should achieve energy balance. Reliable and efficient energy delivery is vital for complex metabolic networks because, in a healthy metabolic network, energy generation and consumption must maintain a continuous balance. Metabolic networks have a complicated control mechanism for preserving a continuous balance between energy generation and demand. Hence, energy balance analysis is very helpful to understand the regulatory and control mechanisms operating in complex, large-scale biochemical systems [44].

In an analogy with metabolic networks, the generation and consumption of energy has to be balanced at all times in an energy delivery network for sustainable healthy social development. The electrical power grid is a primary and widespread type of energy distribution network, with access all the way down to domestic users. In an imbalanced electrical power grid, voltages exceed their lower or upper limits; this damages the generation, transmission or customer equipment and can result in severe power outages and blackouts. In today’s world, a long-term power outage in a region may easily turn become a social disaster due to the great dependence of all appliances on electrical power. This is because all generators and grid loads participate in a very large, complex control system whose task is to maintain energy balance by minimizing area control error [45]. In some recent works, the energy balance problem was discussed on the bases of power generation by a hybrid energy system [9–11,46–48] and the large area distributed control problem [45].

Let $Y'_j$ represent the energy supplement rate (ESR) of the $j$-order node. If the total energy provided by the end users or sub-nodes in node domain is denoted by $C'_j$, and the total energy consumption estimation for the time period $T_E$ in the node domain is denoted by $C''_j$, then $Y'_j$ can be defined as:

$$Y'_j = \frac{C''_j - C'_j}{C''_j}. \tag{1}$$

The parameters $C''_j$ and $C'_j$ are the estimation of the total energy supplement and energy demand of the end user for a period $T_E$ in the future. In this first-order node domain, ESR can be obtained as $Y'_1 = \frac{C''_1 - C'_1}{C''_1}$. When $Y'_1 \leq 1$, the node requires energy and should perform in EC mode in the domain of a higher-order node ($N''_{k+1}$). On the other hand, when $Y'_1 > 1$, the node has redundant energy and can perform in ES mode in the domain. In the case of energy balance in the node, $Y'_1 = 1$.

Let us assume $p$ number of elements in ES mode in the domain of $N''_{i+1}$ denoted by $C''_i$ ($i = 1, 2, 3, \ldots, p$), and $k$ number of elements in EC mode, denoted by $C'_j$ ($i = 1, 2, 3, \ldots, k$). In this case, $C'_j$ can be expressed as:

![Fig. 2. A representation for a tree-like node hierarchy of UMN in the three node levels. Generated energy flows upward and energy flow for consumption is downward.](image-url)
$C_f^i = \sum_{i=1}^{p} (1 - \alpha_g^i) G_i^{i-1}$,

and $C_f^i$ can be written as:

$C_f^i = \sum_{i=1}^{k} (1 + \alpha_g^j) C_f^i - 1.$

Here, the parameter $C_f^i$ is the amount of stored energy of element $i$ to supply for a grid line in ES mode during a $T_g$ period in future. The element in ES mode declares the value of $C_f^i$ to master node $N_i$. The parameter $C_f^i$ is the consumption estimation of element $i$ for a period $T_g$ in the future. The parameters $\alpha_g^j$ and $\alpha_g^i$ are the energy loss rates in the domain of node $j$. The amount of losses sustained in transport, depending on the energy generated and consumed, can be written as $\alpha_g^j C_f^i$ and $\alpha_g^i C_f^i$, respectively.

For a consistent prediction of $C_f^i$, a statistical method based on the previous consumption pattern of end users can be given as follows:

$$C_f^i = \int_{t}^{t+T_g} E[W_j^i(t)] dt,$$

where $E[W_j^i(t)]$ is the expected value of the load profile function of the element $i$ in the node $j$, denoted by $W_j^i(t)$. The prediction of domestic energy generation to supply the grid can be calculated as follows:

$$G_j^i = \int_{t}^{t+T_g} \text{MoS}(E[S_j^i(t)]) dt,$$

where $S_j^i(t)$ is the energy generation profile function of an element. The term $E[S_j^i(t)]$ is the expected value of the generation profile function of element $i$ in node $j$. The function MoS($\cdot$) is an appropriate mode switching function that is determined with respect to the consumer or node-management prerequisites. The MoS($\cdot$) function can be implemented as an intelligent algorithm running domestically in SCCUs. For the end user, functions $W_j^i(t)$ and $S_j^i(t)$ can be compiled from the history of consumption and generation data; these data are stored in the user’s SCCU as a part of the domestic application of DSLM strategies [49]. Satisfactory hour-ahead forecasting of the demand pattern [50,51] and renewable energy generation patterns [5,46,49,52–54] is possible from the long-term past records of end users, as represented in Fig. 3. A representation of $W_j^i(t)$ and its expected value are also presented in Fig. 3.

A reliable energy source with a predefined EAP for all of the first-order nodes in a UMN should satisfy following condition:

$$\sum_{Y^i} (Y^i - 1) = 0.$$  

Let us define a balance error function for all first-order nodes ($\epsilon^1$) as:

$$\epsilon^1 = \sum_{Y^i} (Y^i - 1)^2.$$  

In order to dynamically retain the solution of $\epsilon^1 = 0$, one can define the balance error function for the first-order node $q$ as follows:

$$\epsilon^1_q = \frac{(C_f^1 + \Delta E^1_q - 1)}{C_f^1_q},$$

where $\Delta E^1_q$ represents the energy requirement of the first-order node $q$. Considering that all $\epsilon^1_q \to 0$ results in $\epsilon^1 \to 0$, the energy requirement for the energy balance of the first-order node $q$ is obtained as:

$$\Delta E^1_q = \sum_{i=1}^{k} (1 + \alpha_g^i) C_f^0 - \sum_{i=1}^{p} (1 - \alpha_g^i) G_0^i.$$  

For a globally energy-balanced network, the balance error function to optimize can be written as:

$$\epsilon = \epsilon^1 + \epsilon^2 + \epsilon^3 + \cdots = \sum_{Y^i} (Y^i - 1)^2.$$  

A relevant solution for the global energy balance ($\epsilon \to 0$) in UMN can be written in accordance with Eq. (9) as:

$$\Delta E^i_q = \sum_{j=1}^{i} (1 + \alpha_g^j) C_f^0 - \sum_{i=1}^{p} (1 - \alpha_g^i) G_0^i.$$  

A node in UMN can decide between the ES and EC mode depending on the value of the energy requirement, as in the following:

$$\text{Mode}^i = \begin{cases} \text{ES}, & \Delta E^i_q < 0 \\ \text{EC}, & \Delta E^i_q \geq 0 \end{cases}.$$  

The control function defined by Eq. (12) give the node an adaptation capability for varying conditions of load demand and local energy generation states in its own domain. Thus, the energy flow in UMN is dynamically organized according to varying demands of end users from the bottom to the top of the UMN hierarchy. An example of a UMN energy flow schema on a landscape is illustrated in Fig. 4.

The highest-order node of UMN is referred to as the root node, and the energy reliability of the UMN can be observed with respect to the energy supplement rate of the root nodes, denoted by $Y^1_i$. If a UMN is capable of supplying its dynamic consumer set for a $T_g$ period of time (EAP), it becomes an energy reliable UMN with EAP. The following basic measure ($R_{\text{UMN}}$) can be given for the degree of energy reliability in a UMN:

$$R_{\text{UMN}} = \begin{cases} Y^1_i, & Y^1_i < 1 \\ 1, & Y^1_i \geq 1 \end{cases}.$$  

Energy efficiency in the UMN depends on the losses that are sustained in the energy transport, storage, and management operations. If the energy losses are minimized, UMN becomes an energy-efficient network.

2.3. Properties of energy-balanced UMN

The redundant energy generated by end users flows up to the higher-order nodes in the tree-like hierarchy. Meanwhile, the
energy transported for consumption flows downward to the lower-order nodes. To identify a UMN as energy balanced, it is enough to obtain energy balance at the root node. However, energy balance can take place at lower-order nodes in the hierarchy. Let the energy balance order of a UMN be defined as the minimum order of the node set, where all nodes in this level are energy balanced. For instance, provided that all second-order nodes are balanced but at least one first-order node is imbalanced, this UMN will be a second-order energy-balanced network.

As a result of the tree-like architecture of the UMN, if a UMN is j-order energy balanced, all higher-order nodes \( (j + 1, j + 2, \ldots) \) up to the root node become energy balanced as well. This is because all j-order nodes work in the islanded mode and there is no need for energy transport among the higher-order nodes. This feature is termed upward-balance spread. Accordingly, when the UMN reaches first-order balance, the widest upward-balance spread will occur for the UMN and all higher-order nodes will reach the energy-balanced state.

A UMN will be energy reliable when it reaches energy balance at any order. Thus, the order of energy balance does not deteriorate energy reliability. The balance order of the UMN has an influence on energy efficiency since it can decrease overall energy transport losses. The lower-order energy balance becomes more energy efficient due to the decreasing energy transports among the higher-order nodes. Overall energy transport loss rate for an n-order energy-balanced network is expressed as,

\[
a^2_l = 1 - \prod_{i=0}^{n} \left(1 + a^2_i\right) \left(1 - a^2_i\right)
\]

Fig. 5(a) demonstrates the relation between energy transport losses depending on node balance orders. Energy savings rate in the first-order balanced UMN, when considering the energy transport losses rates of the n-order balanced cases, can be defined as \(a^2_l - a^2_1\).

An estimation of energy savings in the first-order balanced UMN is illustrated up to 10th-order balance in Fig. 5(b). This figure reveals that the first-order energy balance provides remarkable energy saving from energy transport losses comparing to the higher-order balance of UMN.

The following remarks can be made in relation to the UMN modeling of the smart grid concept:

i) Optimal energy balance is obtained when all nodes in the network are energy balanced \( (c^* = 0) \); this refers to a first-order balanced UMN, and implies that all nodes work self-supportively and generate as much energy as is demanded. No redundant energy is generated in the nodes. This feature decreases the waste of energy in storage, and hence will have a positive impact on the greenhouse effect. The first-order balance of UMN can be achieved by employing self-supportive microgrids. This is why the energy balance problem for the optimal solution can be simply reduced to the problem of energy balancing in the microgrids.

ii) In the case of an imbalance in a great portion of first-order nodes, second-order nodes may retain energy balances via the support of highly generative first-order nodes. Energy losses in the energy transport operation among the first-order nodes will decrease energy efficiency in comparison to the optimal balance, but the UMN will still be energy reliable. If the imbalance state proceeds to the root node and the energy supplement rate of root node becomes lower than one \( (Y^*_1 < 1) \), the UMN becomes unreliable for period \( T_g \).

As long as the energy balance of the UMN is retained only for the highest-order node, the UMN will maintain energy reliability in a less efficient way due to high energy transport losses. In order to promote the energy balance of the first-order nodes (islanded microgrid operation), which is the most energy-efficient state of UMN, the energy price at a node domain can be regulated corresponding to the order of energy balance. In the literature, as an example study for the design of an electric market of smart grid, a general economic equilibrium model based on control theory techniques was addressed by Wang et al. [55].

### 2.4. Controllability and user prioritization

A decentralized network architecture based on a tree-like node hierarchy facilitates both the real-time control and monitoring operations of a large-scale network infrastructure. This is because each node deals with lower-order nodes (sub-nodes or slave nodes) in its own domain [24,29,30,56]. This local management strategy greatly reduces the number of parameters that need to be collected,
analyzed, and responded to by the administration. In order to retain energy balance, each sub-node declares its energy requirement \( \Delta E_i \) and ESR values \( Y_j \) to its master nodes. Thus, a root node has information about the global energy status of the whole network. This bottom-up local reporting approach will facilitate network state estimation.

A very critical question that should be asked is as follows: What will happen if the UMN is not reliable for a noticeably long period of time \( Y_r < 1 \)? In such a case, there will not be enough total energy generation for the total energy demand of the consumers during EAP. At this time, the first-order node might organize the energy flows according to a user prioritization protocol, such as preferential end users and standard end users. In the case of an energy shortage, energy resources might be allocated to supply preferential end users for EAP. For instance, hospitals and government offices might be identified as preferential end users, and energy will therefore be supplied to them. The remainder of the energy reservoir might be allocated to be shared fairly by the standard users.

In a conventional analog grid, generators drive the loads directly, and any operation or abnormality on one part of the grid easily influences the rest of the system. This is a factor that reduces the controllability of the grid due to the difficulty of estimating the outcomes of an operation in a large-scale dynamical analog system. However, DESs allow the grid to be fractionated in terms of signal continuity and power flows via charge buffering and signal synthesis. Thus, such digitized power flows facilitate not only controllability and observability, but also the fault isolation and self-healing capability of the system. These will be main benefits of digitized power network as a smart grid [57].

3. Energy balance analysis of the UMN for smart grid applications

3.1. Energy balance analysis for stochastic end-user behaviors

In this section, a probabilistic energy balance analysis of a third-order UMN is presented for the case of uncertainty in user modes. Such uncertainties in the character of end users make them stochastic elements. The probabilistic analysis of networks constructed by a stochastic end-user population will be helpful in illustrating possible network conditions [48].

The test grid consists of 1000 end users that are clustered by 50 first-order nodes. The first-order nodes are linked by 10 s-order nodes to a root node at the third-order. This network configuration can be expressed by the vector of \([1000 50 10 1]\). The mode selection of stochastic end users is carried out with respect to a uniformly distributed random number \( Rnd \) in the range of \([0,1]\) as the following:

\[
\text{Mode}_i^\text{ES} = \begin{cases} \text{ES}, & Rnd \leq P_{ES} \\ \text{EC}, & Rnd > P_{ES} \end{cases}
\]  

(15)

where \( P_{ES} \) denotes the probability of being in the ES mode. The random energy generation and demand profile of the stochastic
end user are modeled as \( \text{Rnd} \ E_{\text{ES}} \) and \( \text{Rnd} \ E_{\text{EC}} \), where \( E_{\text{ES}} \) and \( E_{\text{EC}} \) represent hourly average energy generation and average energy consumption, respectively.

The average household energy consumption of a family in Europe is about 5 kWh (\( E_{\text{EC}} = 5 \) kWh). A hybrid energy system composed of a wind turbine and photovoltaic array can generate an average energy of 5.6 kWh according to daily profiles reported in [46] (\( E_{\text{ES}} = 5.6 \) kWh). Energy transport losses in the first-order node were set to 6\% (\( a_1^1 = a_1^1 = 0.06 \)), the losses in the second-order nodes were set to 6.5\% (\( a_2^2 = a_2^2 = 0.065 \)), and the losses in the third-order nodes were set to 6.7\% (\( a_3^3 = a_3^3 = 0.067 \)). (Transmission and distribution losses in the USA were estimated at 6.6\% in 1997 and 6.5\% in 2007 according to data from the U.S. Energy Information Administration.)

The average ESR values \( Y_1 \) of the node groups versus the various probabilities of the ES mode \( P_{\text{ES}} \) are presented in Fig. 6(a). The impacts of the energy transport losses were observed as decreasing the average ESR values with respect to node orders. Hence, the transition of the higher-order nodes to ES mode will be possible at larger \( P_{\text{ES}} \) probabilities due to increasing energy losses in transport. Fig. 6(b) reveals the rate of ES mode transition of nodes occurs at a higher \( P_{\text{ES}} \) probability of

with RB label in Fig. 6(a) and (b). However, the UMN is still not energy efficient. The UMN becomes a second-order reliable network at \( P_{\text{ES}} = 0.63 \) (roughly 63\% of stochastic end users are in the ES mode), and finally reaches first-order reliability at roughly \( P_{\text{ES}} \geq 0.74 \). This implies that UMN can work in islanded operation, and hence in the most energy-efficient way, when 74\% of stochastic end users are in ES mode. This probability forms a boundary to the maximal efficiency explained as optimal energy balance in Section 2.3. The dashed line with EB label in Fig. 6(b) represents the maximal efficiency boundary.

Fig. 7 illustrates the impacts of high transmission losses on the energy reliability of UMN. In this test, \( a_1^1 = a_1^2 = 0.20 \), \( a_2^2 = a_2^3 = 0.23 \), and \( a_3^3 = a_3^4 = 0.25 \) are used; it is observed that the ES mode transition of nodes occurs at a higher \( P_{\text{ES}} \) probability of
end users. The network reaches a reliable state at roughly $P_{ES} > 0.73$, as shown by the dashed line labeled EB in Fig. 7(b). The divergence of ESR values $(Y_i)$ due to transmission losses can be observed more clearly in Fig. 7(a). As transmission losses decrease, the reliability boundary of the UMN approximates $P_{ES} \approx 0.5$ and the ESR values of the node converge. Alternating ES–EC mode transitions of the root node, as shown by the solid circle in Fig. 7(b), may appear as a result of the random fluctuation of the energy generation and consumption profiles.

Fig. 8 reveals the impact of low average generation profiles ($E_{SE} = 2.1$ kWh). The reliability boundary moves to $P_{ES} = 0.78$, implying that when the energy generation capability of the stochastic end user is comparably lower than the energy demand, more end users should be in the ES mode to make the UMN an energy reliable network.

### 3.2. Case study for the energy balance analysis of several generation scenarios

In this section, an energy balance analysis of a third-order UMN is conducted using hourly load and generation profile data obtained from the Capo Vado site, which is located in the windiest region of Liguria, Italy [53]. At this site, there is high energy generation potential from the renewable resource mix (wind + solar). Stochastic end users in the UMN with a configuration of [1000 50 10 1] were characterized by a random deviation in the load and generation profiles of Capo Vado. By employing 5% deviation in wind-based energy generation, 2.5% deviation in solar energy generation, and 5% deviation in consumption profiles, the end-user consumption and generation patterns were randomly generated for 1000 end users, as shown in Fig. 9. The loss rates of $\alpha_1^1 = \alpha_1^2 = 0.06$, $\alpha_2^1 = \alpha_2^2 = 0.065$, and $\alpha_3^1 = \alpha_3^2 = 0.067$ were used in the calculations. The energy assurance period (EAP), $T_e$, was assumed to be 24 h.

Fig. 10 reveals the ESR values for the first- and second-order nodes; these were calculated from the end-user generation and consumption profiles given in Fig. 9. It was observed that if the end users have significantly higher generation profiles than consumption profiles,

![Fig. 10](image-url)

**Fig. 10.** Calculated $Y_1^i$ in (a) and $Y_2^i$ in (b) for the stochastic end-users profiles in Fig. 9. For root node, $Y_1^1 = 5.70$.

![Fig. 11](image-url)

**Fig. 11.** Average generation and demand profiles of the stochastic end-users in (a), calculated $Y_1^i$ and $Y_2^i$ in (b) and (c). For root node, $Y_1^1 = 1.05$.

![Fig. 12](image-url)

**Fig. 12.** Average generation and demand profiles of the stochastic end-users in (a), calculated $Y_1^i$ and $Y_2^i$ in (b) and (c). For root node, $Y_1^1 = 0.52$. 

![Fig. 8](image-url)

**Fig. 8.** Reveals the impact of low average generation profiles ($E_{SE} = 2.1$ kWh). The reliability boundary moves to $P_{ES} = 0.78$, implying that when the energy generation capability of the stochastic end user is comparably lower than the energy demand, more end users should be in the ES mode to make the UMN an energy reliable network.
profiles, all nodes will be in ES mode and the UMN will be first-order energy balanced. This region is very suitable to be a renewable energy provider site for higher-order UMN installations.

Fig. 11 reveals an analysis of the case of a tenfold reduction in average energy generation in the generation profiles for Capo Vado shown in Fig. 9(b). The average generation and consumption profiles of the end users are plotted in Fig. 11(a). In this condition, the UMN will still be first-order energy balanced. However, although the first-order nodes can work self-supportive, it is not suitable as a renewable energy provider for a higher-order UMN installation because $Y_{i}^{1} = 1.05$ at the root node. Thus, this UMN can hardly maintain the energy reliability.

Fig. 12 presents the analysis results obtained in the case of a 20-fold reduction in average energy generation in Capo Vado’s profile. The average end-user profiles are illustrated in Fig. 12(a). At this energy generation level, the UMN will not be capable of maintaining energy balance during EAP (24 h) in any node because $Y_{i}^{1} < 1$ for all nodes. The ESR of the root node decreases to 0.52 due to transportation loss. The grid resources provide about half of the total energy demand required for the EAP time. This is why the grid will be unreliable and continuously demand energy from higher-order UMN installations.

In order to repair the energy balance of the unreliable UMN analyzed in Fig. 12, the end-user with the index of 500 is configured to be an energy compensation station with an energy generation profile of 100 times that of Capo Vado’s average generation profiles. Fig. 13 shows that this compensation station will increase the average energy generation of the UMN to a degree, which makes the UMN third-order energy balanced, with $Y_{i}^{3} = 1.58$. If necessary, an energy compensation station installation based on renewable resources is recommended to compensate for local generation shortages. This station also supports the energy reliability of UMN in the case of any abnormality such as a transmission fault.

4. Conclusions

In this paper, a promising smart-grid architecture system was presented on the basis of UMN with a tree-like node hierarchy. The energy balance and energy reliability of the grid were discussed for the case of stochastic end-user modeling, along with several variants of the Capo Vado end-user profiles. Many properties of energy balance in the UMN were revealed and the energy reliability and energy efficiency under uncertain generation-demand conditions were evaluated theoretically.

The network architecture discussed and the interconnection-interaction policies defined are observed to be very convenient in the realization of DG, DES, and DSLM applications for future smart grids. Management based on the ESR, energy balance error, and node energy requirement parameters is very useful in terms of handling uncertainty in generation profiles, which results from the volatility of distributed renewable energy sources and the uncertainty in consumption profiles due to the variety of dynamic appliances. These parameters will facilitate not only real-time monitoring and management operations over the whole of the network, but also the analysis and planning of a reliable smart grid infrastructure. In future studies, these parameters might become a basis for the development of possible optimization algorithms to resolving the optimal energy flow problems for reliable and efficient energy distribution.

Isolating consumer load from a line signal via DES will be a basic step in digital power networks where energy flow from generation to consumption is not continuous. The charge flow is interrupted by DESs and can be restored using buffered charges in any synthesized waveform and any direction by means of user-mode switching. Currently, this technology seems to be costly; however, it might become affordable and even profitable in the future owing to advances in material science and nanotechnology.

Although in this paper the authors focused on future energy delivery grids, specifically smart grids, the presented methodology on energy balance and energy balance-oriented flow mechanisms might be useful in the analysis of other complex networks involving uncertainty and variability, such as biological or social networks.

References
