A Two-Level Fuzzy Logic Machine-Based Control Algorithm for Resilient Microgrids in ICT Applications

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Abstract Resilient microgrids have been the subject of growing interest from information and communications technology (ICT) service providers to assure service availability (and therefore revenue) even in the case of grid fault due to bad weather conditions, as an internal storage capacity as uninterruptible power supply is used. However, such storage equipment represents an unavoidable cost in terms of initial investment, maintenance, and operational efficiency. In this work, starting from a previous development of a prototype supply system for a landline station, the control algorithm of the storage devices was investigated to optimize the cost/benefit ratio. A fuzzy logic system controller was developed to exploit the revenue opportunities offered by the energy market, converting a landline station into an active system that exchanges power through the grid. Besides this, a fuel cell generator was integrated to achieve further benefits (system resiliency and battery size reduction). The simulation results indicated a well-reactive behavior for energy price, battery state of charge, and grid fault probability variations.

1 Introduction

Nowadays, ICT equipment (e.g., radio base stations, data centers) needs stable and continuous power supply, usually assured by dedicated storage systems. However, such systems represent an additional cost to their owner and operator. From the customer's point of view, the economic losses are caused by service interruption, while from the operator's point of view, the extra costs are connected to contract penalties toward their customers [1].

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Usually, the main causes of system downtime are ascribable to the weather conditions [2], and even in the last decade, enormous phenomena such as floods and hurricanes caused lot of system downtime events.

In a distributed generation (DG) scenario (as in [3]), microgrids can take an active part on the grid regulation, as users ("prosumers" in this case). Such an optimization process may be accomplished both by the hardware design (e.g., by energy content and power peak value for the storage system, nominal power for the internal generation system) and by the control logic to regulate the energy flows through the grid exploiting the installed resources (generation and storage). In this view, assuring both UPS functions and grid services, the design should be addressed to provide the system with resiliency features. Despite not still defined by international standards, "resiliency" (or "resilience") has operational definitions (for critical infrastructure), as in [4–6], rooting in the concurrent presence of robustness, resourcefulness, and rapid recovery (in case of disruptive events) of the assessed infrastructure. Indeed, since the unexpected occurrences are mostly grid faults, this process would be based on a predictive algorithm approach that, in literature [7–9], leads to the development of not fully deterministic control logic techniques, but is based on the probability of the event occurrence.

Among these techniques (artificial intelligence) to implement predictive algorithm, fuzzy logic (FL) has the capability of mapping blurry concepts in membership sets and, as reported in Tables 1 and 2, appears flexible enough to support the resilience implementation in systems operating in a DG scenario. This feature suggests using FL to exploit weather forecast report data (such as rain probability, expected wind and sky clarity, and so on) to guess if a grid fault has a relevant occurrence probability or not.

Table 1 Literature comparison between FL and other approaches/techniques

Other approaches in literature	Difference with fuzzy logic (FL)
Hardware redundancy: supporting the distribution system by decentralized plants and even combining the two approaches [10]	FL implies absence of cost of new hardware (since fuzzy logic control algorithm can be implemented on very cheap controller). Moreover, hardware redundancy is usually (in literature) represented by additional microgrid (i.e., nodes) to support the electric distribution system
Artificial intelligence (AI) techniques	FL belongs to artificial intelligence approach; a more detailed comparison among these techniques is presented below and in the main text
Demand response (DR) incentive (for power delivery) scheme in an energy market to simplify the load forecast [11]	Incentives to DR (to simplify load forecast) can be included in FL, but their value (per time step) is "modulated" by weather conditions and system state (SoC in our case)

Table 2 Literature comparison between FL and other artificial intelligence techniques

Other AI techniques (references in squared brackets)	Reason to prefer fuzzy logic (FL)
Artificial neural networks (ANNs)—e.g. [12]	ANNs require long training to learn system behavior. Moreover, due to the rarity of the forecasted events, the number of faults in the training data is exiguous even with a lot of input combinations
Multi-agent system (platforms) (MAS)—e.g. [13]	These platforms improve the overall grid resilience, but are not adequate to enhance the single node (as addressed by the present work). FL, operating local optimization (even thanks to the simplified dataset), has quicker response representation. Moreover, they require continuous data exchange between nodes that can be absent during the emergency states (that is the target of the proposed investigation)
System with inductive learning (IL)—e.g. [14]	IL requires sensor network and, therefore, besides the cost increment, can (successfully) only work at run-time. However, it is a good alternative once the design and set-up phase is concluded

In parallel, the exploitation of storage capacity availability (i.e., the expected idle/emergency state, according to the weather prediction) can be optimized by an algorithm based on the data coming from energy market (buying and/or selling price) in the "day-ahead" price databases. FL was used to integrate the price value in the overall control algorithm, as detailed in the following discussion. The developed algorithm was addressed to model the hybridization of a battery with a solid oxide fuel cell (SOFC) system as source of internal generation (whose prototype and load profile were already studied in a previous work [1]) and to optimize the storage capacity operation.

The block diagram of the prototype is reported in Fig. 1 and the load profile in Fig. 2. In this work, the control and optimization by artificial intelligence are presented.

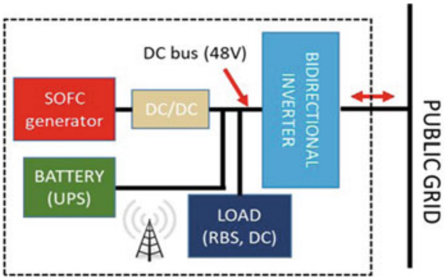

Fig. 1 Block diagram of the hybrid power supply system and connections to load (telecommunication station) and electric grid

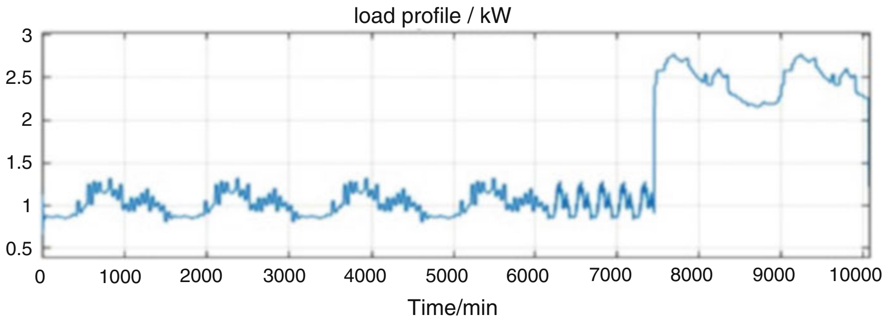

Fig. 2 Telecommunication station load profile. The peak load period occurs during the weekend; this depends on the positioning of the station on the territory. The choice of such unbalanced distribution represents an additional challenge to the hybrid system design

2 Numerical Simulations

2.1 Data Overview

To evaluate the potential benefits of the above-mentioned approach, a simulation tool was developed in MATLAB Simulink environment.

The FL algorithm was implemented by using the following four signals (Tables 3, 4, and 5 show the partition of each overall signal span into overlapping intervals):

For this reason, the FL algorithm has been modified to be fully operative only in a large range, but not 0–100%. Besides this, the thresholds would allow the system (in the perspective of more flexible energy market) to have a reservation of capacity both to store and release power from and to the grid. From the overall logic point of view, the algorithm was based on a two-level FL scheme (Fig. 3), i.e., a first layer that, based on the weather forecast signals, only determines if the grid faults have a relevant probability to occur or they should be negligible, respectively identified as "resilient" or "normal." Such states identify the operation mode of the latter FL layer. The latter FL layer has two FLMs (FL machines) to determine the charge/discharge rate of the battery. The charge or discharge operation is the algebraic result of the difference between actual load and internal power production

Table 3 Membership function assignment (first-layer FLM)

Variable	Description
Wind sp. speed	From a weather station near the installation site and distributed in five intensity intervals
Weather signal	Combination of "sky clarity," "rain probability," and "rain intensity" from weather report
Energy price	Varies according to the "day-ahead" price of the Italian energy market for electrical power production/consumption [15]
State of Charge (SoC)	The actual storage (battery) SoC that is particularly critical once the usually unused capability (UPS function) is utilized to support the grid services

Table 4 Membership function assignment (first-layer FLM)

Variable	Membership intervals (overlapping with different probability)				
Wind sp. (m/s)	Low <3	Moderate 2–7	Average 5–11	Intense 7–18	High >11
Weather signal	No rain		Moderate		Heavy rain
Mode (OUTPUT)		Normal >0.4		Resilient <0.6	

Table 5 Membership function assignment (second-layer FLMs)

Variable	Low range		Medium range	High range	
SoC% (min max)	0 30	25 40	35 60	50 80	70 100
Price/c€/kWh	4–6		5.5–8		7–12
Grid disconnection expectation	0–0.3		0.22–0.6	0.5–1.0	

(fuel cell generation). In each time step, the "net load" (negative when FC generation power is greater than the actual load power) must be satisfied by the algebraic sum of the power from battery and power from grid. The simulation was performed by using 3-min time slots. This output acts like a switch for the latter-level FLM that defines the normal or the resilient fuzzy mode algorithms. The forecast signals were collected to determine the state profile (*normal*/*resilient*) by a first fuzzy logic machine whose inputs are the weather (as a linear weighted combination of sig_wx and rain probability) and the wind speed; both (input) signals are reported in Fig. 4. Wind speed, weather signal, energy price, and battery SoC were converted into partially overlapping intervals named after logic labels, explained in the following single-layer FLM descriptions:

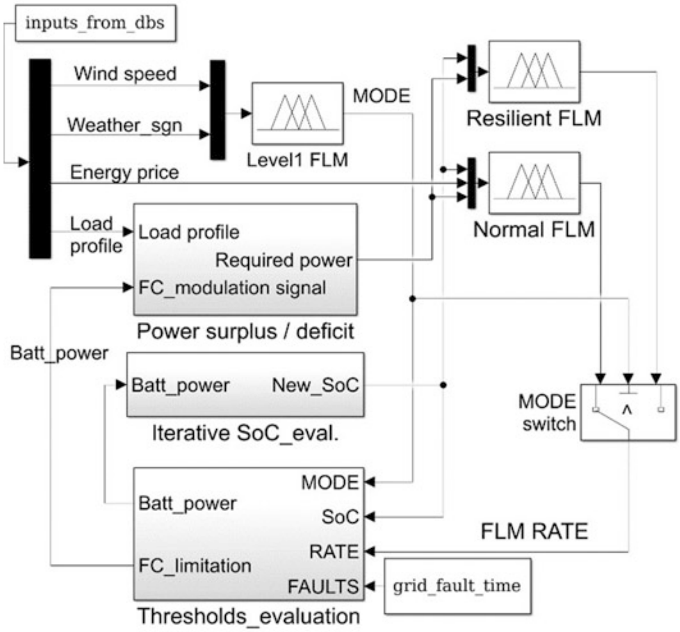

Fig. 3 Implemented two-layer fuzzy logic controller ("normal" and "resilient" modes). During "emergency" mode (i.e., grid outage), the FL is bypassed to, since the only function is the surviving of the load (telecommunication station)

2.2 *Implementation of First-Layer FLM: Raw Signals from Weather Forecast—Collection and Treatment*

The two input signals of the first-level fuzzy machine (weather and wind) were elaborated, through the tabled fuzzy rules (inference engine), to determine a single output and select the operation mode of the controller (i.e., the system state: *normal* or *resilient*). This signal was associated to a "fuzzy" threshold (with a smooth transition in the range of 0.4–0.6, as indicated in Table 4) for the defuzzification process. The resulting (output) mode profile is reported in Fig. 5.

2.3 *Second-Layer FLM: Signals from Energy System: Collection and Treatment*

In the second layer of the fuzzy controller, the overall algorithm distinguishes a *normal* and a *resilient* operation state and determines how the discrepancy (either surplus or deficit) between the actual generation and the load consumption is

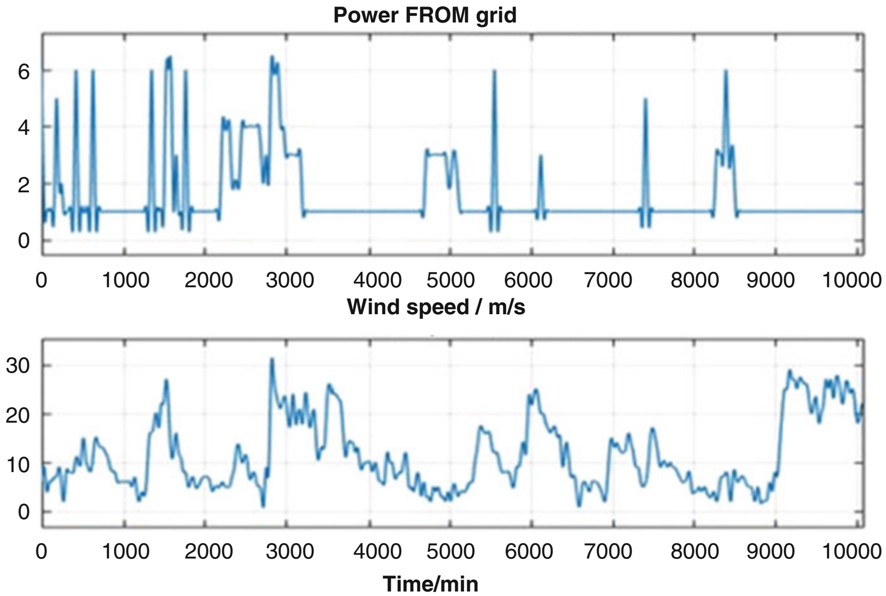

Fig. 4 Weather signals recorded (1 week) as input variables of the first layer of the FLM (the corresponding output is the operational mode "normal/resilient")

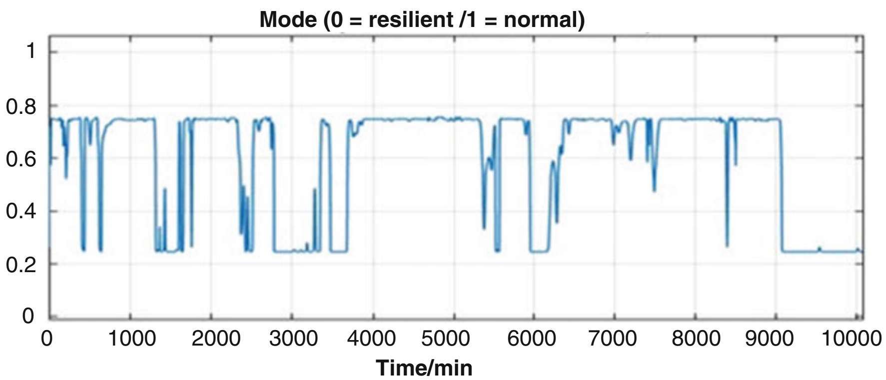

Fig. 5 Operational mode (*normal*/*resilient*) as output of the first-layer FLM. This signal switch (in each time step, 3 min) between the two corresponding control algorithms

distributed between the battery and the grid. Thus, it requires actual energy price (recorded with hourly base for a week, Fig. 6) and SoC as input variables.

The battery SoC values were divided into five intervals and the selected membership functions are in Table 5. To cover the whole span of each variable, the intervals are overlapping, like in Table 5.

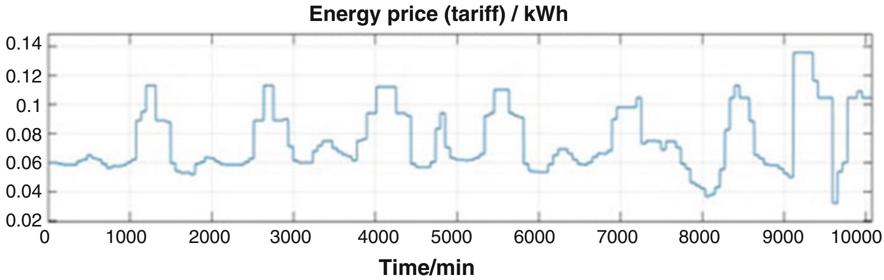

Fig. 6 Weekly profile of the energy price (c€/kWh) in the considered week (one sample per hour)

Table 6 Power surplus/deficit distribution (battery charge/discharge rate)

Interval name	Actual grid current/nominal battery current
Battery $\gg$ grid	0–0.4
Battery > grid	0.2–0.55
Balanced	0.45–0.67
Battery < grid	0.55–0.9
Battery $\ll$ grid	0.8–1.0

To define a correspondence between the input and the output variable intervals, this approach requires a table of rules (listed by a priority order) to univocally assign the combination of two or more input variables to a single output interval. Such rules work as Boolean combination of membership functions within "IF … THEN" conditional statements, as in [16]. For example if the wind speed is "high" and weather is "storm," the response will belong with high probability to "resilient"; otherwise it will belong with lower probability to it if they are, respectively, "average" and "moderate." Analogously, in the second layer, if SoC is low, price is low, and there is a surplus, the grid rate tends to charge the battery with a higher current; when the price is "high" ("low"), the grid power request decreases (increases) consequently. On the other hand, in "resilient" mode the FLM aims to bring the SoC to high values. The target is injecting the surplus preferably to increase the battery SoC instead of toward the grid, regardless of the energy price. The output variables result in a variation of the batteries' charging/discharging power, through a "defuzzification" process, which is able to translate the output states in numbers to control the actuators. Except for the extreme values of the SoC (qualitatively described above), the fuzzy layer determines the distribution of the power surplus/deficit between batteries and grid, whose "nominal" interval limits are highlighted in Table 6.

Basically, since the resilient case has relevant expectation of a forthcoming grid failure, the algorithm does not take into account, as visible in Fig. 3, the energy price. On the contrary, the "threshold and emergency controller" evaluates, in the *resilient* mode only, an extra function "fast charge" to accumulate more energy (since the probability of a grid fault is relevant) in the batteries to overcome the grid fault periods. This defuzzification threshold value (0.4) was set to bias the control logic toward a conservative mode and adapted to trigger the "fast charge output." Indeed, the "fast charge function" determines an interruption of the basic fuzzy logic to start an extra charging process. Moreover, if the grid failure occurs, it is necessary to consider an emergency state that is determined by the absence of energy exchange through grid, so that the battery SoC is a direct consequence of the power surplus/deficit.

3 Results

To analyze the behavior of the FLM in different cases, in the simulation, different artificial grid faults were forced. This was done to assess the effect of correct (*resilient* state) or wrong (*normal* state) outage prediction impact on the surviving capability of the system.

3.1 Analysis of Extreme Cases in Normal Mode

However, in case of extreme values of the considered variables (e.g., battery SoC greater than about 85% or lower than about 30%), the algorithm optimizes the storage capacity utilization for grid services by reducing the effect of the variable "energy price" in the decision algorithm. To analyze this criticism of the algorithm, the implemented simulation was performed in the normal mode only. This is visible in the plots in Fig. 7. In A, A′, and A″ sections, due to the very high SoC (those peak values reach 85%), the system injects (for just one time slot per peak) power to the grid even if the price is low to discharge the battery a little and avoid the probability of being unable to offer reserve capacity to the grid.

On the other hand, in section B, despite the high price of energy, the system prevents the battery from deep discharge to preserve both capacity for grid services and battery life, as well as the residual capacity from further displacement that would be detrimental for the necessary (even short) UPS function in case of an abrupt disruptive event.

3.2 Dynamic Behavior of the System to Abrupt Signal Variation

A close-up on a valuable price variation (Fig. 8) allows to verify the effect of an abrupt (decreasing) variation of the hourly energy price. For instance, in the time window from minute 4000 to 4500, the discrepancy between generated and consumed power has some sign variations and the energy prices move quite rapidly

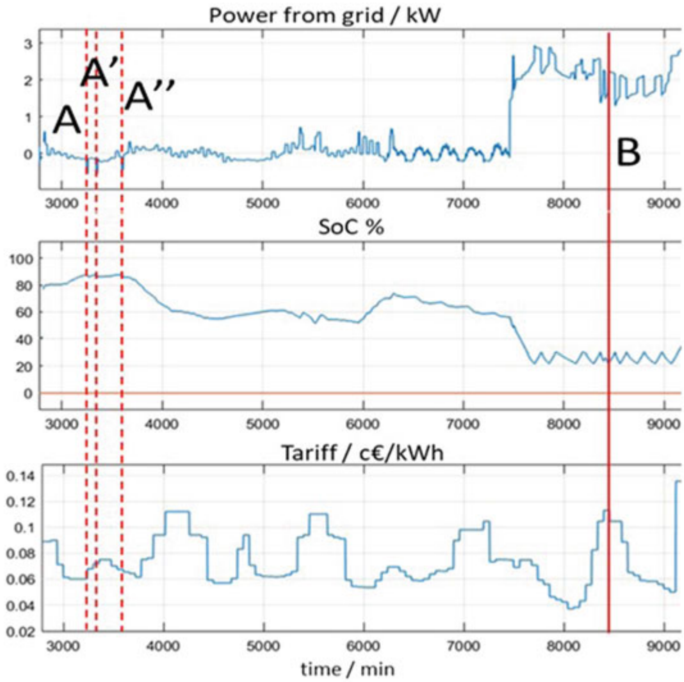

Fig. 7 "Normal" mode—effect of different SoC: in A, A′, and A″ the power is injected into the grid even at low energy price, due to the compensation effect of the high SoC. In B, extremely low SoC makes the system to inject power into grid even at low price

from the highest values to the minimum. The comparison of the plots ranging around 4100–4250 shows that while the fuel cell generation exceeds the load consumption, since the price is high, the power surplus goes entirely to the grid (i.e., SoC is constant). In particular, it is evident that, due to the rapidly diminished energy price, despite a positive discrepancy between generation and load, the power drained from the grid has an increasing trend, so that the low energy price signal is interpreted as the right time to re-charge the battery with higher power instead of injecting power to the grid. Hence, in this case, the battery is re-charged both from grid and SOFC generator. On the contrary, in the time slots in which the load exceeds the FC generation, the most part of the necessary power comes from the battery and a small part (with a decreasing trend) from the grid (this is because the SoC is in the intermediate range).

Moreover, once the price has its most relevant drop (around minute 4260), the grid contribution to load supply increases and the battery contribution decreases. These two results demonstrate that fuzzy logic controller has effective consequences both in long-time observation windows and in fast dynamics (comparable with the examined phenomena).

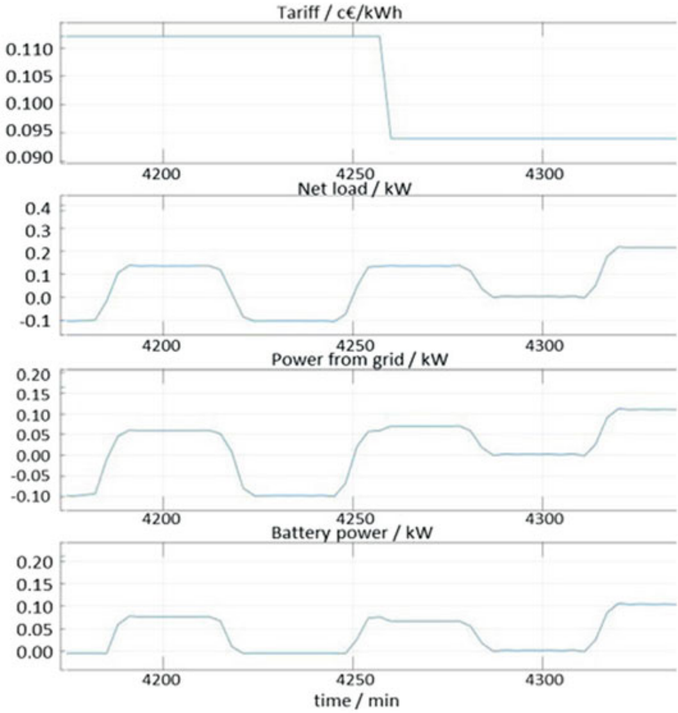

Fig. 8 At high energy price values, the battery injects power to the grid. Once the energy price abruptly drops, even if the load requires more power than the FC generation, the grid is used to contemporarily supply the load to re-charge the battery

3.3 Analysis in Emergency Mode: Limits, Constraints, and System Corrections

Since in *emergency* mode the fuzzy control system cannot operate, only solutions at system level were implemented. Due to the very unbalanced profile, the selected load profile can severely stress the storage regulation.

In particular, two opposite case have been simulated:

1. A long grid failure occurs while the SoC has *very high* value, in a working day.
2. A long grid failure occurs while the SoC has *intermediate* value, during the weekend with high power consumption.

In the former case, as visible in Fig. 9, the SoC may reach 100% due to the average excess of the generated power with respect to the average load in the working days. For this reason, in Fig. 9, from section A to section B, since the grid power must be zero, the battery SoC would increase over 100%. Therefore, the algorithm was refined to balance this point with a programmed (in slow steps,

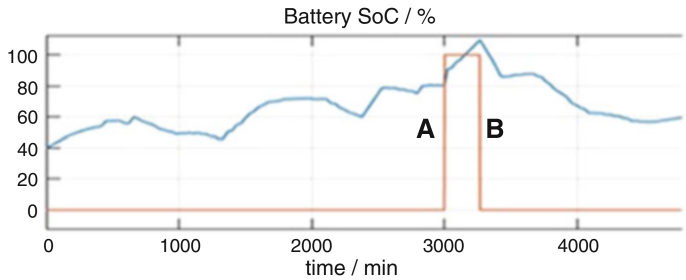

Fig. 9 Emergency mode—SoC drift due to the low load consumption over time without the possibility of injecting generation excess into the grid. The correction is operated by limiting the SOFC production in compliance with the system dynamics

compliant with manufacturer indications) reduction of fuel cell power generation down to half of the nominal power to limit the battery SoC increment. Such correction introduces a loss of efficiency in the energy conversion process, but lets the algorithm operate without risk of being shut-down to avoid malfunctioning.

The carried out analysis highlighted that, to be compliant with the power dynamics indicated by the manufacturer, it is possible to set a SoC threshold value of 87% to start the power generation reduction. However, this event occurred (in Italy) extremely rarely in the last few years.

4 Conclusions

In the presented work, a control strategy based on fuzzy logic was developed and analyzed to exploit the storage resources (UPS/battery) to provide energy services to the grid while satisfying the regular necessity of continuous operation of a landline station for telecommunications. To reach an appropriate balanced goal between revenue from energy market and service surviving, a fuzzy logic-based algorithm was tested against different conditions of the system operation. In particular, during normal operation, the controller outputs were analyzed at the most rapid variations of the energy price, to verify the adaptation of the battery charging/discharging rate regulation even according to the SoC value evolution. Weather, price, consumption, and generation were considered to calculate the energy flows through the battery and the grid. This led even to discharging battery toward load and grid in case of high price and high SoC or, in contrast, draining power to satisfy the load in case of low energy price depending on the battery SoC. On the other hand, the *resilient* working mode, acting as a pre-alert state, did not include the energy cost in the battery rate calculation, since the system downtime is considered (in those time slots of the simulation) by far disadvantageous than the purchase from grid even at high price. Concerning the *emergency* mode, it was studied by forcing grid outage periods at different combinations of weather forecast signal, power load, and energy price levels, to analyze the effect of the weather forecasting and FL, reducing the probability of service down-time.

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References

1. G. Brunaccini et al., Modeling of a SOFC-HT battery hybrid system for optimal design of off-grid base transceiver station. Int. J. Hydrogen Energy **42**(46), 27962–27978 (2017)
2. F.H. Jufri et al., Analysis of determinants of the impact and the grid capability to evaluate and improve grid resilience from extreme weather event. Energies **10**(11), 1779 (2017)
3. B. Brooks et al., Incorporating user utility in a smart microgrid with distributed generation and elastic demand, in *2017 IEEE International Conference on Communications Workshops (ICC Workshops)*, (IEEE, Piscataway, NJ, 2017)
4. https://www.dhs.gov/sites/default/files/publications/niac-critical-infrastructure-resilience-final-report-09-08-09-508.pdf
5. ENISA, *ENISA Report. Measurement Frameworks and Metrics for Resilient Networks and Services. Technical Report* (ENISA, Heraklion, 2011)
6. H.H. Willis, K. Loa, *Measuring the Resilience of Energy Distribution Systems* (RAND, Santa Monica, CA, 2015)
7. T. Wang et al., Neural networks for power management optimal strategy in hybrid microgrid. Neural Comput. Applic. **31**, 2635 (2019)
8. L. Hernandez et al., Short-term load forecasting for microgrids based on artificial neural networks. Energies **6**(3), 1385–1408 (2013)
9. P.-C. Chen, M. Kezunovic, Fuzzy logic approach to predictive risk analysis in distribution outage management. IEEE Trans. Smart Grid **7**(6), 2827–2836 (2016)
10. M. Mukherjee et al., Distributed generator sizing for joint optimization of resilience and voltage regulation, in *2018 North American Power Symposium (NAPS)*, (IEEE, Piscataway, NJ, 2018)
11. X. Yang et al., A novel microgrid based resilient Demand Response scheme in smart grid, in *2016 17th IEEE/ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, (IEEE, Piscataway, NJ, 2016)
12. S. Zarrabian et al., Real-time smart grids control for preventing cascading failures and blackout using neural networks: experimental approach for N-1-1 contingency. Int. J. Emerg. Elect. Power Syst. **17**(6), 703 (2016)
13. S. Rivera et al., A multi-agent system transient stability platform for resilient self-healing operation of multiple microgrids, in *ISGT 2014*, (IEEE, Piscataway, NJ, 2014)
14. W. Kohn et al., A micro-grid distributed intelligent control and management system. IEEE Trans. Smart Grid **6**(6), 2964–2974 (2015)
15. http://www.mercatoelettrico.org/it/
16. D.G. Schwartz, A system for reasoning with imprecise linguistic information. Int. J. Approx. Reason. **5**, 463–488 (1991)