A Comparison of Status Update Optimization and Microgrid Management

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***Abstract*—Provision of timely power supply to digital networks through smart microgrids represents a relevant research challenge. In next generation communication systems, high power demands are caused by the need for an efficient management of real-time content and guaranteeing up-to-date context awareness to computationally heavy applications. Such an integrated communication-energy challenge is gaining momentum in the research community, but, possibly due to different timescales, the problems of energy provision and data networking are often investigated with different approaches and mindsets. In this paper, we argue that they both stem from a fundamentals problem of efficient resource management that can ultimately be treated via dynamic programming as a unifying analytical tool. To this end, we show how the problems of energy management in a smart microgrid can be tackled through a framework conceived for the optimization of age of information. This allows to infer useful conclusions and, at the same time, the similarity can be expanded to leverage existing analytical procedure and derive efficient approaches, especially concerning the insertion of distributed intelligence in the control mechanisms.**

***Index Terms*—Smart Grid; Energy management; Energy harvesting; Age of information.**

I. Introduction

In the rapidly evolving digital age, the effective management of information and energy has become crucial for various domains. Next generation communication systems are expected to provide many user-oriented services in contexts such as the Internet of things (IoT) [1], autonomous vehicles (AVs) [2], augmented/virtual reality (AR/VR) [3], eHealth and mHealth [4], and smart grids (SGs) [5].

While the specific challenges of all these applications may vary, some common trends can be identified. In particular, energy provisioning represents a notable challenge, due to the strong power-hungry character of many next generation communication systems. This requires to leverage renewable energy options to avoid an excessive use of fossil sources, and energy storage units controlled by intelligent management techniques for compensating downtimes [6]. For this reason, the architecture of reference becomes that of a smart microgrid, i.e., a localized energy system that integrates renewable generation as well as storage through batteries and connection to the grid, along with advanced monitoring, control, and communication technologies [7]. It operates on a smaller-scale than the conventional power grid, providing electricity to a specific geographic area, possibly for communication oriented and/or mission critical purposes. For these reasons, its prompt availability of energy is important [8].

At the same time, most of the aforementioned applications revolve around timely delivery of data to the end user, which is key for real-time content and the exploitation of the correct ambient awareness in context-based applications [9]. This also prompts the search for representative performance metrics characterizing the freshness of exchanged data. For this reason, the Age of Information (AoI) metric is becoming increasingly popular in the study of communication systems [10], [11].

AoI is a performance indicator used in networking to quantify the timeliness or freshness of information at a receiver in a communication system. It is defined as the time elapsed since the generation or update of the most recent piece of information at the source, measured at the receiver's end [12]. As such, it is a crucial metric in real-time applications and has gained significant attention in the field of information theory and network optimization to analyze the timeliness of information delivery. As a result, many studies exist where the general goal is to minimize AoI, by controlling data injection under specific constraints.

Although seemingly distinct, these two problems, namely AoI minimization and energy management in smart microgrids, share commonalities that allow them to be framed as inventory problems and analyzed as dynamic programs [13], [14]. In this paper, we explore and compare them, highlighting their similarities and discussing the application of dynamic programming as a unifying analytical tool.

We consider a problem, originally conceived for AoI [15] but actually translated to the case of microgrid management, of scheduling a finite number of replenishment opportunities over a given time window so as to maximize the average reward given by energy availability. We consider a scenario where some opportunities are lost with independent and identical distributed failure rate, due, e.g., to lack of availability from the grid. We compare an offline (pre-determined) solution and the online optimal policy for this problem. The solution obtained by dynamic programming within this formalization permits to

This work was supported by the European Union under the Italian National Recovery and Resilience Plan (NRRP) of NextGenerationEU, partnership on "Telecommunications of the Future" (PE0000001 - program "RESTART").

gain useful insight about the role of side information for the system status when dealing with microgrid management. Also, it emphasizes the importance of prediction mechanisms in the energy supply [16].

In summary, the minimization of AoI and the optimization of energy management in smart microgrids can both be framed as inventory-like problems using dynamic programming techniques. By framing these challenges within the inventory management framework, we gain valuable insights into their underlying similarities and leverage dynamic programming as a unifying analytical tool [17]. This approach not only enables us to address these complex problems efficiently but also opens avenues for cross-domain knowledge transfer and the development of innovative solutions at the intersection of information theory and energy management.

We also envision that game theory can play a crucial role in this context, due to the simultaneous presence of multiple agents (e.g., consumers, producers, and grid operators) able to make decisions that impact the overall system [18]. The inventory problem can be extended to a multi-agent case through a game-theoretic framework to model and analyze the strategic interactions of distributed players [19]. Through this approach, our considerations for the energy provisioning in a smart grid can be extended to encompass multi-agent scenarios, paving the way for the development of advanced distributed algorithms that can effectively manage smart grids in real-time, accounting for uncertainties and complexities within the dynamic environment.

The rest of this paper is organized as follows. Section II gives some background on the scenario and dynamic programming applications. The problem formulation and proposed approach is shown in Section III. Some sample numerical results are shown in Section IV. Finally, the paper is concluded in Section V.

II. Background

Smart microgrids use advanced technology and communication systems to improve the efficiency, reliability, and sustainability of electricity generation, distribution, and consumption [20]. The key task in their management can be seen as the maximization of energy availability at any given time, which relies on energy storage to preserve excess energy during periods of low demand and releasing it during peak demand [21]. This can be seen as an inventory problem, generally characterizing the reservoir of energy resources. The challenge lies in determining the optimal allocation and release of stored energy to meet fluctuating demands, striking a balance between energy availability and cost-effectiveness.

AoI quantifies the freshness of information in a communication system, representing the time elapsed since the most recent update at the receiver [10]. The problem of minimizing AoI-related values, such as the average AoI over an operation cycle, can also be viewed as a reverse inventory problem. In traditional inventory management, the goal is to optimize the allocation of resources over time to meet future demands, while in the AoI problem, the focus is on minimizing the time since the last update to maximize the freshness of information. This poses intriguing parallels between the two problems.

Moreover, dynamic programming provides a powerful framework for solving inventory problems by breaking them down into smaller subproblems and finding optimal solutions through recursive computations. Its application to the AoI problem and energy storage in smart grids allows us to tackle these complex challenges using a common analytical approach [15].

In the AoI problem, dynamic programming can be employed to determine the optimal scheduling of information updates, minimizing the AoI metric over time. By formulating the problem as a sequence of decision points, where each decision determines the next update time, dynamic programming algorithms can be designed to optimize the update schedule and minimize the AoI [11].

Similarly, in the context of microgrid management, dynamic programming techniques can be used to optimize the allocation and release of stored energy based on anticipated demands, price signals, and other relevant factors. By considering the trade-off between energy availability, cost, and system constraints, dynamic programming algorithms can find the optimal energy release schedule that minimizes costs while ensuring reliable energy supply [8].

Dynamic programming is a mathematical optimization technique used to solve problems that can be broken down into overlapping subproblems. Both AoI optimization and energy provisioning in a smart microgrid exhibit these characteristics, making them suitable candidates for the application of dynamic programming. Both can be seen as the overlap of multiple subproblems. The decision to replenish the energy storage or refresh the current status information is made periodically based on the current energy level/AoI and the expected system evolution [17]. The optimal decision strategy can be determined by considering the future evolution into smaller subproblems with shorter timespan and/or stocking levels.

In this sense, one can think of applying Bellman optimality criterion [22] exploiting that the best solution to the overall problem can be constructed based on the optimal policies of the individual subproblems. Dynamic programming allows for the construction of an optimal solution based on the principle of *backward induction*, i.e., a recursive formulation, where the problem is decomposed into smaller subproblems and solved iteratively. Moreover, the solutions for both problems can be solved in practical cases through the memorization or tabulation of an optimal policy based on the system state. This allows to implement practical solution whose time and space complexity is kept under control thanks to the recursive formulation.

III. Problem Setup

The problem of energy supply from external sources in a smart microgrid can treat the energy resources as inventory items, where the smart microgrid has a maximum storage set to a value B that can be thought of as the capacity of the energy storage elements (batteries and the like). The goal is to manage the availability and utilization of resources over time, so we set a reward function that is just the energy level available to the microgrid. Naturally, this can be changed, e.g., to severely penalize energy outages or overflows [23].

The energy demand within a smart microgrid can fluctuate based on various factors, including user consumption patterns, weather conditions, and time of day. On the supply side, the availability of energy from external sources is subject to factors such as grid connectivity, grid stability, and energy purchase agreements. Balancing the supply and demand of energy within the microgrid requires efficient management of the inventory of external energy resources [24]. For the sake of simplicity, in this analysis we consider a linearly decreasing constant usage of energy availability, in line with standard inventory problems, until energy is replenished by an acquisition from an external source in the whole grid.

For a smart microgrid, energy from external sources needs to be replenished to maintain a sufficient supply to meet the energy demands. This can be achieved through mechanisms such as purchasing energy from the main grid or receiving energy from other connected grids. The process of replenishment ensures that the microgrid has an adequate inventory of external energy resources [25].

We also note that we set a limited number of such replenishment opportunities. For the sake of formalization, we set a whole time window observation of N time instances (hereafter called slots) and the replenishment can only be performed on at most m of such instances, with $m \ll N$. A similar problem of scheduling refreshment instants has been tackled already in [15] for AoI minimization over a finite communication window. The similarities in the finite horizon are due to the need of a tight-knit control for practical systems, whereas the limit in the number of replenishment opportunities, which in AoI minimization can be justified by the duty cycle constraint of wireless devices, can be related in smart microgrid to the need for limiting energy injection from external sources, possibly due to the presence of multiple microgrids with the same requirement.

The objective of the management can be directly related to the energy level available to the smart microgrid, as this translates to optimizing the utilization of energy from external sources to minimize energy loss or oversupply [21]. One option would be to define an offline (stateless) plan of replenishment, i.e., to identify m time instants out of the N available as those where the replenishment from an external source takes place. We assume that replenishments set the available energy in the microgrid to a maximum available capacity B, which is akin to the standard inventory problem. Also, we assume that in between replenishment instants, the energy availability decreases at the rate of 1 unit per slot.

If this is the case, the setup of the m replenishment instants denoted as $\tau_1, \tau_2, \ldots, \tau_m$ corresponds to choosing $m+1$ variables $y_0, y_1, \ldots, y_m$, where $y_j = \tau_{j+1} - \tau_j$, with the convention that $\tau_0=0$ and $\tau_{m+1} = N$ and the constraint that the y_js sum to N. This can be framed as a constrained optimization, where the objective function is chosen as the availability of energy in the smart microgrid, thus can be formalized as

$$\max R(\mathbf{y}) \quad \text{s.t.} \sum_{i=0}^{m} y_i = N \tag{1}$$

where $R(\mathbf{y})$ is the average reward, computed as

$$R(\mathbf{y}) = \sum_{\mathbf{c} \in \{0,1\}^m} \prod_{j=1}^{m} (1-f)^{c_j} f^{(1-c_j)} \cdot \sum_{k:c_k=0} \frac{\big(2B - \min(z_k, B)\big) \min(z_j, B)}{2N} \tag{2}$$

where

$$z_k = \sum_{h=k}^{\min\{N, k \leq h : c_h = 1\}} y_h \,. \tag{3}$$

To explain (2), one can observe that all the possible outcomes of success/failure over m attempts are considered by bitmap $\mathbf{c}$, with 0 representing a failure and 1 being success. The average reward is computed as the integral over N slots, normalized to N. Given the linear descent of the reward, the integral results in the triangular pattern computed in (2), where the z_js terms are defined in (3) as the sum of all subsequent y_j with failures inbetween (since the summation stops at the first successful replenishment instant). The minimum in (2) follows from the energy level never going below 0, which causes the maximum side of the pattern to be equal to B. Problem (1) is easy to solve via numerical methods as, besides some non linearities induced by the minima, it is actually a system of quadratic equations, hence the gradient is pseudo-linear.

Conversely, an online optimization strategy can follow a dynamic programming approach to determine the replenishment. The problem can be cast into the definition of an optimal control for a system state, also in the presence of noise corresponding to missing replenishment due to energy unavailability [22]. The system state at time t is set as $x(t) = \big(R(t), \xi(t)\big)$, where $0 \leq R(t) \leq B$ is the temporary reward at time t, and $\xi(t)$ is the number of replenishment opportunities left available at t, for which $\xi(0)=m$. The system control $u(t)$ results in a binary choice between replenishing at epoch t or not [11], while noise is captured through the failure probability f.

The system evolution from $x(t)$ can be written as
(i) $x(t+1) = \big(R(t)-1, \xi(t)\big)$ if no replenishment is attempted at time t (i.e., $u(t)$=0). In this case, we assume that the energy level simply decreases by one at each epoch. This can be complicated with more advanced models.
(ii) $x(t+1) = \big(R(t)-1, \xi(t)-1\big)$ if $\xi(t) > 0$ a replenishment is performed at time t (i.e., $u(t)$=1), but it is unsuccessful, which happens with probability f. The same energy descent model as (i) is assumed here.
(iii) $x(t+1) = \big(B, m(t)-1\big)$ if $m(t) > 0$ and replenishment is successful, which happens with probability $1-f$.

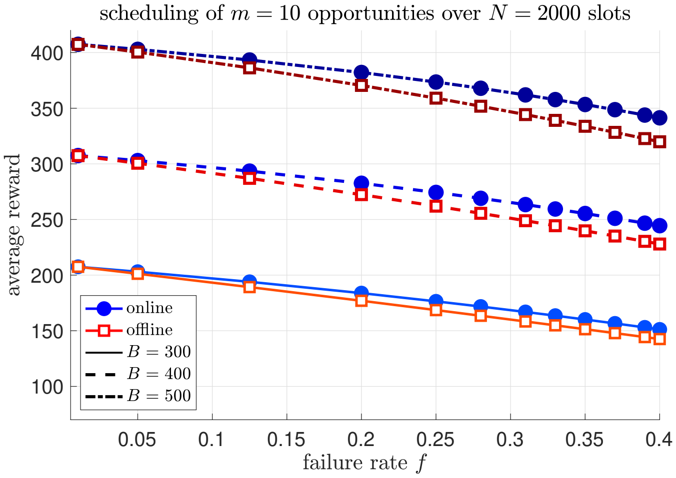

Fig. 1. Comparison of online vs. offline scheduling of m=10 opportunities over N=2000 slots for different inventory levels.

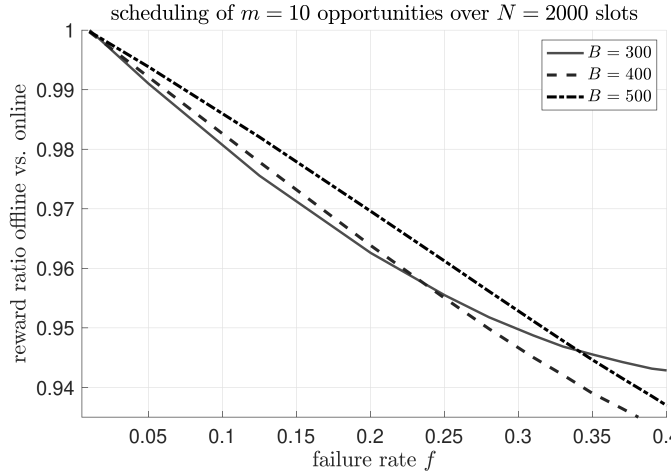

Fig. 2. Ratio of online vs. offline scheduling rewards, m=10 opportunities over N=2000 slots for different inventory levels.

This is essentially an inventory problem that can then be solved by finding the optimal control policy $\mu_t(x(t), f)$ to apply at state $x(t) = \big(R(t), \xi(t)\big)$, as the strategy maximizing the expectation over N epochs of reward $g_t\big(x(t), u(t), f\big) = R(t)$. To achieve this, the standard procedure is to exploit Bellman's optimality condition [22], since if the optimal policy is described by $\mu_0, \mu_1, \ldots, \mu_{N-1}$, then for any value of $x(t)$ at time t, $0 < t < N$, occurring with positive probability, the optimal policy from t till N is $\mu_t, \ldots, \mu_{N-1}$.

At a given state $x(t)$, the reward-maximizing policy is

$$\mu_t\left(x(t), f\right) = \mathbb{1}\Big[(1{-}p)\,\mathcal{C}_{t+1}\big(R(t){+}1, \xi(t){-}1\big) + p\,\mathcal{C}_{t+1}\big(B, \xi(t){-}1\big) < \mathcal{C}_{t+1}\big(R(t){+}1, \xi(t)\big)\Big] \quad (4)$$

where

$$\mathcal{C}_t\big(x(t)\big) = \sum_{i=t}^{N} g_i\Big(x(i), \mu\big(x(i)\big), f\Big) \quad (5)$$

and $\mathbb{1}[\cdot]$ is an indicator function, equal to 1 if the condition inside is true, 0 otherwise. In other words, the optimal control at time t is achieved by making the decision that minimizes an expected total cost equal to the AoI, assuming future decisions are optimally made and averaging over channel errors [15].

The only actions for the border cases $x(N{-}1) = (R, m)$ with $m > 0$ and $x(t) = \big(R, 0\big)$ are to replenish and not to replenish, respectively. Thus, one can start by assigning μ for these cases and apply backward induction to find the best online replenishment policy for all states at every t. It is important to remark that such an approach assumes fixed system parameters, yet even parametric drifts, which are common in energy trading scenarios because of price fluctuations and energy availability [24], can be accounted for by leveraging on results available for other problems, such as AoI [17].

IV. Numerical Results

We instantiated the problem of energy provision in a smart microgrid by assuming linear energy usage of 1 energy unit per time epoch, and availability of energy replenishment that follows a Bernoulli failure model, where every attempted replenishment is failing according to an i.i.d. process with probability f.

As sample results, we consider the case of N=2000 time epochs, with an upper limit on the replenishment attempts m equal to 10. We adopt different values for the maximum energy storage in the smart microgrid B, taken equal to 300, 400, and 500 energy units respectively. We compare the solution of the offline problem with predetermined replenishment instants with an optimal online policy achieved through backward propagation in a dynamic program.

Fig. 1 considers the average reward obtained for different values of the microgrid storage capacity and compares the offline and online scheduling of replenishments. It is visible that the two solutions are in agreement, being identical when the failure rate f goes to zero, but even for significantly higher failure rates, the difference is overall limited.

To better elaborate on this trend, we consider in Fig. 2 the ratio of the two curves, which can be seen as a quantification of the loss of efficiency due to setting the replenishment instants in advance, as opposed to adjusting them online. Notably, the loss of efficiency is within 10% and saturates to higher values when f increases if the storage capacity is limited. This happens because lower storage capacities result in more frequent outages. A possible extension of this result can consider an additional penalty if outages are encountered and/or to include the minimization of the outage probability in the problem's objective [23], [25].

V. Conclusions and Future Work

The inventory problem is a classic example of dynamic programming as containing overlapping subproblems, which is possible to solve through optimal substructure and recursive formulation. Energy management in a smart microgrid can be tackled by framing it within this context, and applying dynamic programming principles. This allows the provision of optimal strategies for managing energy demand and supply and making informed decisions regarding energy replenishment and control.

As preliminary results, we considered the scheduling of a constrained number of replenishment opportunities in a smart microgrid over a finite time horizon, with the objective to maximize energy availability. We focused on a scenario with linear energy usage over time and full replenishment of the storage capacity, with i.i.d. probability of missing updates to energy unavailability [15]. However, these assumptions are easy to relax and more complicated models can be considered instead. We compared an offline and online solution to the problem of scheduling replenishment instants, showing that, for the considered model, the loss of efficiency when considering a preliminary assigned replenishment pattern is limited. However, it becomes relevant when the system is more-failure prone, which seems to suggest that practical solutions in contexts where energy supply is erratic require a closely monitored stateful management [24].

Moreover, even a stateless optimization of the replenishment pattern in a smart microgrid would require precise knowledge of the system characteristics. Therefore, our results imply that it is important to acquire an overall description of the microgrid ecosystem, possibly through unsupervised learning [16], to properly manage the energy supply.

Future work may involve a stateful optimization of the energy replenishments, where the energy storage of the microgrid is taken into account through dynamic programming to determine the optimal supply policy at run-time. Alternatively, an interesting avenue for future studies is the application of game theory to the case of multiple uncoordinated sources [19]. This may lead to understanding the efficiency (or lack thereof) of systems where multiple agents, e.g., associated with multiple providers, traders, and/or energy sources, can all contribute to the replenishment of the microgrid [26].

In its broadest meaning, game theory can also extend its applicability to encompass security issues for smart grids [27]. In the aforementioned scenario, where multiple agents can provide energy to the microgrid, the system becomes more susceptible to malicious threats and vulnerabilities [28]. Game theory provides a valuable tool to model and analyze the strategic interactions between actors seeking to exploit weaknesses in the smart grid or to obtain illicit financial gain and defenders aiming to prevent this from happening.

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