Controlling Smart Grid Adaptivity

Hermen A. Toersche, S. Nykamp, A. Molderink, J. L. Hurink, and G. J. M. Smit

***Abstract*—Methods are discussed for planning oriented smart grid control to cope with scenarios with limited predictability, supporting an increasing penetration of stochastic renewable resources. The performance of these methods is evaluated with simulations using measured wind generation and consumption data. Forecast errors are shown to affect worst case behavior in particular, the severity of which depends on the chosen adaptivity strategy and error model.**

***Index Terms*—Energy management, linear programming, smart grids, wind energy.**

I. INTRODUCTION

FACING increasing stress on the electricity grid, academia and industry propose a *smart grid* paradigm, aiming to improve the economy of the electricity supply chain by using information and communication technology.

Current developments make the smart grid paradigm increasingly attractive and make it more and more become reality. On the demand side, a large scale electrification of larger domestic appliances (a.o. heat pumps [1]) and electric vehicles increase the electricity demand significantly—and increases the opportunities for demand side management. On the supply side, inflexible and variable renewable producers are emerging. Consequently, the increased flexibility on the demand side ought to be used to balance the flexibility decrease at the supply side.

A pivotal aspect in exploiting the economic potential of the smart grid is resource dispatch management, which is the theme of this work. Common optimization objectives include load balancing (decreasing production and transport inefficiencies) and dynamic pricing exploitation. Literature has proposed several management strategies, showing substantial improvements over passive control (Section II). The "TRIANA" approach developed at the University of Twente (Section II-B4) complements these approaches with spatial hierarchical planning. The fitness of this approach has been illustrated before [2], [3], [4].

To exploit the available flexibility within the system, a forecast of future system constraints is needed, i.e. expected supply and demand. Next to being variable over time, the total supply and demand are both also hard to predict precisely. Discrepancies between the projected and realized behavior are inevitable and can result in problems. This paper addresses this issue in the context of TRIANA. For the use cases considered so far, these problems could be safely ignored. Projected cases with more volatile conditions—already existent in parts of the US [5]—do not permit this abstraction.

We propose to extend the planning oriented approach to accommodate more dynamic environments, aiming to improve the following aspects of TRIANA:

- **Economy:** Tighten acceptable safety margins and exploit better-than-expected circumstances.
- **Scope:** Support scenarios which particularly benefit from or depend on dynamic response, including (dynamic) real time pricing and demand response.
- **Dependability:** Increase the ability to circumvent problems using local and collective flexibility.

In this paper, we introduce the general concepts towards adaptive smart grid control. These are illustrated and partially validated in an economy-oriented context. For the sake of brevity and completeness, a full treatment of the latter two aspects is deferred.

We first provide an overview of the background of the problem (Section II). Subsequently, we explain the need for adaptivity and its aptness in contexts with variable uncertainty (Section III), followed by a discussion on strategies for realizing a tractable solution for the problem (Section IV). These are evaluated using simulations (Section V). We close with conclusions and recommendations for future work (Section VI).

II. BACKGROUND

In this section, we first reiterate the smart grid context (Section II-A), followed by an overview of the control approaches presented in related work (Section II-B).

A. Context

As stated in Section I, *smart grid* refers to novel abilities to monitor and control the electricity supply and demand. It is furthermore associated with several accessory resource and context changes. Some of these changes are material to this work and are treated here. A more complete overview is provided in literature, see [6].

1) Supply: Renewable resources commonly have limited production adaptation flexibility. Natural causes make solar and wind conditions subject to variability, translating to a variability in electricity production. This leads to serious infrastructure problems. In Germany the frequency of congestion incidents, where large renewable energy producers are contracted to reduce their infeed with conservation of payment to avoid imbalance problems in the transmission and distribution grid, is increasing [7].

Furthermore, for the renewable resources, production profile predictions are not perfect, as these depend on weather forecasts. While generally the accuracy of these is reasonably

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good [8], substantial outliers with poor predictability do occur [9]. The resulting uncertainty needs to be accounted for. The current market design affords an increase of the capacity of swift response generation facilities, i.e. gas plants. However, due to a low number of operating hours, the profitability of these plants is questionable leading to investment restraints of market participants [10].

2) Demand: Demand side control offers ample flexibility opportunities. Because (retrofit) smart appliances are required, this is presently only extensively used beyond trials for large industrial loads. Three appliance classes are covered extensively in literature: thermal systems, batch job appliances and electric vehicles (EV).

In this work, we abstract from demand side management, i.e. it is regarded as a potential implementation of storage. Furthermore, we approximate that the demand side is fully predictable based on the law of large numbers. All relevant nondeterminism is imposed by the supply side.

3) Storage: To offset unanticipated *and* anticipated deviations, buffering is needed. Demand and supply response provide this feature implicitly. In addition explicit storage is considered, involving a tradeoff between capacity, efficiency (instantaneous and over time), electricity market conditions and capital costs.

Abstaining from going into the details of specific technologies, we presume economical efficient large scale electricity storage to be infeasible at present. Storage should therefore be economized.

4) Pricing: Electricity suppliers (and markets) use variable tariff structures to avoid being penalized for occurring imbalances in demand and supply. Various schemes have been proposed with an increasing degree of sophistication, ranging from Time of Use (TOU) pricing to real time pricing and critical peak pricing, incurring severe penalties for (excess) on-peak consumption. These have already been implemented in parts of the US [5].

The trend observed in these programs is that technology improvements enable electricity price volatility to be shifted to the end users and shifted forward in time. This means that financial benefits can be attained by revising behavior as cost expectations change.

5) Dependability: Electricity prices are irrelevant when the supply fails. The disconnection of mission critical loads causes substantial economic damage in the US and in developing countries [11], [12]. Furthermore, in numerous applications intermittence results in disproportionate losses. Therefore some (incentive-reinforced) altruism in maintaining grid stability seems prudent.

In practice, critical facilities are protected with emergency power supply hardware (UPS and diesel generators)—at substantial cost. As an alternative, literature proposes to establish microgrids, reusing distributed energy resources (DER) for dependability purposes. This approach promotes economy of scale and increases flexibility [13]. To exploit this flexibility effectively, appropriate adaptive control ought to be employed.

B. Control

After defining which resources are (to be) available in a smart grid, the next concern is defining how to direct these. In the past, technical constraints limited control to a small number of large producers and industrial loads. With decreasing hardware costs, interest is shifting to residential loads, and in particular to the large household appliances. Consequentially, as the optimization problem size increases *by orders of magnitude*, scalable scheduling techniques need to be devised.

In the following, we provide a brief overview of established approaches for smart grid control problems, referring to literature for a more complete review [14]. We subsequently present our approach, contrasting it to related work and positioning it in this work.

1) Transactive Control: The transactive control paradigm proposes to schedule resources using an interactive electricity double-auction procedure [15], [16]. Distributed software agents place demand and supply bids on a market where the equilibrium price for electricity is determined by an auctioneer. Bidding functions express the local control option desirability.

While being scalable and capable of swift contingency response, assuming that communication is available or can be substituted, the distributed architecture makes it difficult to exclude emergent behavior completely [17]. Transactive control provides load balancing in the spatial dimension and employs a heuristic approach in the temporal dimension, which is encoded in the appliance cost functions. Great attention must therefore be paid to the cost function design and analysis of their interaction in the target context to ensure that the desired behavior is attained for minimizing the global objective.

2) Model Predictive Control: Various groups are studying the unit commitment and the economic dispatch problem, and formulate it as a mathematical optimization problem which can be solved with general techniques.

Control actions affect the state of the system, and should therefore be considered not only in the light of the instantaneous consequences, but also of the effective change in state. In the smart grid control problem, comfort and economy reasons dictate that the local state is to be observed in particular. Considering this, several authors propose to apply Model Predictive Control (MPC), evaluating the immediate and indirect outcome of control actions, typically using a Mixed Integer Linear Programming (MILP) optimization approach.

In a real time constrained context, MPC introduces several issues. The computational intensity of the optimization problem grows (in the worst case) exponentially both with control variables and horizon length. This means that, in order to provide timely results, MPC is typically used with a shallow horizon and a small number of control options. Furthermore, in a distributed context, monolithic concurrent optimization is not feasible. The approach to offset this is to partition and solve MPC problems independently (hierarchical and distributed MPC), for example using pricing based schemes to decouple the subproblems. When price elasticity is too high, this introduces issues. Although good results have been reported in many practical scenarios, performance and stability guarantees are mostly missing [18].

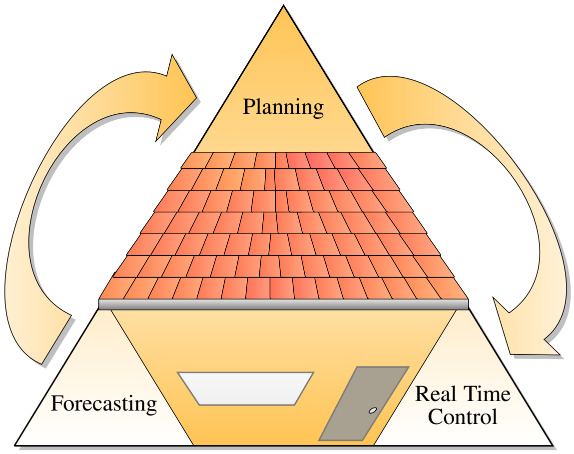


Fig. 1. Three step methodology TRIANA.

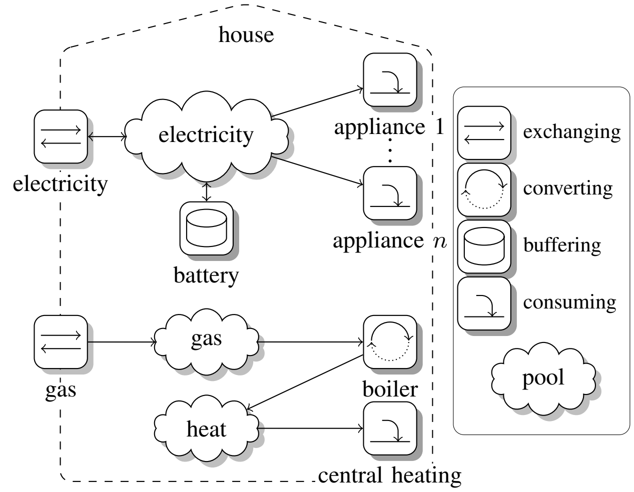


Fig. 2. Example of a TRIANA house model.

3) Stochastic MPC: The need to account for resource behavior uncertainty (*disturbances*) in a predictive setting beyond reevaluation (i.e. closed loop control) has earlier been identified and addressed in the context of the work on MPC. An approach proposed in literature is to incorporate likelihood information in the MPC procedure itself. Rather than deriving the expectation of the input variables, it has been proposed to optimize on the expectation of the cost function, which is hard to express directly in practical cases. A procedure to approximate the latter with randomized realizations has been defined [19] and applied to a (small) energy scheduling problem [20]. As this procedure further aggravates the computational burden (exponentially), it was found that only small problems with short horizon lengths can effectively be tackled. Scalability is left as an open research problem.

4) Distributed, Planned Control: To enable the optimization of the schedule of a fleet of (in particular large domestic) flexible appliances in a scalable manner, the domain specific optimization framework for smart grids "TRIANA" has been developed at the University of Twente over the last half decade (Fig. 1) [2], [3]. The main differentiating feature of this work is that it makes and maintains an explicit electricity profile planning in advance.

The TRIANA framework is modular with respect to application scenarios and optimization objectives. The software associated with the optimization framework provides a graphical user interface to construct simulation scenarios with a standardized representation (Fig. 2). As a result, a multitude of use cases can be and have been covered, including microCHP virtual power plant production scheduling and various demand response scenarios.

The TRIANA approach partitions the smart grid optimization problem into three steps:

- **Forecasting:** Assess the energy demand and other system parameters for the coming period at an appliance granularity [21].
- **Planning:** Determine a dispatch schedule based on the distributed system forecast [22].
- **Control:** Dispatch the resources (in real time), following the dispatch schedule or a local cost optimization [2].

The TRIANA approach has several benefits:

- **Limited communication:** Communication is optional. It is desirable to establish a planning periodically (e.g. once per day), but there is no absolute reliance on real time communication. In emergencies a fail safe alternative may be followed.
- **Predictability:** The electricity profile is established in advance, improving predictability and enabling day-ahead electricity market trade.

Disadvantages include the computational burden of the induced large scale planning problem and the limited adaptivity in the presence of disturbances. This work proposes to rectify the latter at the cost of increasing communication and computation overhead while retaining communication fault tolerance and predictability.

In this work, we focus on determining the impact of forecast errors when using planning with real time control. Scalability and distribution concerns are only addressed from a conceptual point of view in this paper.

III. Rationale for Adaptivity

Planning mismatch can in many cases be desirable or even be inevitable. In this section, we discuss these circumstances.

A. Volatile Objectives

On advanced electricity markets (Section II-A4), prices are determined in real time (as opposed to static or day-ahead time of use pricing). Under the assumption that the optimization objective depends on the clearing price, it is useful to incorporate updated information as it becomes available.

This applies in particular when large differences occur between expected and actual electricity prices. Several US grid operators already issue emergency response requests on critical summer days to shed air conditioning loads, incentivized with grave price penalties [5]. A planner with adaptivity in mind can make preparations for such (anticipated) events and act upon them.

Although real time pricing is the prime considered application in this context, objective volatility is a generic concept.

For example, it becomes useless to operate a light when all residents leave. In the context of the scenario considered in Section V, the objective is static.

B. *Mismatch Response for Minor Deviations*

Device models are not perfect. The physical variability of appliances and operating conditions as well as modeling abstractions result in differences between the estimated and the actual system behavior. We assume that the power consumption difference is typically relatively small and can be averaged out with increasing scale.

Perturbations do build up over time, affecting local state in particular. The TRIANA approach currently assumes that the system state mismatch is reasonably small and can be met with buffer safety margins. This mostly implies that either the planning horizon is limited or the safety margins are overdimensioned (dictated by the magnitude of uncertainty).

With adaptivity, these disadvantages of planning may be reduced. Device behavior can be adapted to mitigate these deviations. Furthermore, if the performance is better than anticipated, we may exploit this to improve on the objective.

C. *Mismatch Response for Major Deviations*

Some resources inherently have a high degree of unpredictability (a.o. Section II-A1). While this may be offset with ample storage, economy and efficiency considerations lead to a preference of adapting the system schedule with more accurate forecast information.

With the availability of ample storage, improved scheduling using updated information can still allow for better use of the available resources.

D. *Volatile Constraints*

In the US as well as in developing countries, power infrastructure problems and (resulting) failures are quite common. Failure is probable during disasters and peak demand (and *supply*) events. The latter becomes an immediate problem when inadequate safety margins are maintained or insufficient capacity is available altogether.

More generally, power infrastructure faults can be regarded as a stochastic process which reconfigures the topology of the power infrastructure. Consequently, the constraints on the application of the resources in the grid are subject to change. Substantial changes substantially affect the operating environment and therefore demand adapted behavior.

Resource degradation can occur gradually over time or instantaneously. When this is known in advance (including the extent over time), this can still be accommodated in a static planning. Otherwise, in a (highly) nondeterministic context, it is not realistic to expect a planning to cover every possible outcome. A lack of perspective on the actual outcome during the planning phase will result in overly pessimistic resource utilization, a demand for excessive storage facilities or failure due to resource exhaustion (or a combination thereof).

This naturally leads to an approach where (final) decisions are postponed to allow the most recent information to be exploited. This does not mean that planning has no value and should not be done. A planning can still accommodate the (approximate) most probable outcomes, or prepare for contingencies under consideration of expectations. Balancing between these is a matter of assigning weights to objectives.

Based on an updated forecast, one may discover that the current schedule becomes unattainable in the (near) future and that it is not possible to avoid failure. Rather than waiting for the failure to occur, one may opt to degrade preemptively in order to mitigate its impact. For example, a battery resource can be spared to serve important loads.

IV. Towards Adaptive Control

In a nonideal environment, discrepancies persist between planning and reality. Under favorable circumstances these can be effectively masked with buffer margins, abstracting undesired behavior.

Accepting reduced predictability, the latter approach becomes ineconomical. Better techniques should therefore be considered and evaluated. We shortly present a more elaborate vision on coping with these disparities in the future. More specifically, we consider techniques which may be described as *adaptive control*. By swift diversion from the planned behavior without full replanning, rapid response to changing conditions may lead to improvements on the objective.

A. *Planning State Interception*

As the planning detoriates over time with respect to the real system state, corrective action is demanded. Behavior could be adapted to return to the predestined state. The flexibility for correcting the state can be sourced both locally or in the near vicinity, violating the planning of the affected devices. Selecting the devices to affect, one may prefer devices which are easy to replan.

Exhausting the flexibility of neighboring systems, the option should be available to request an upstream electricity profile change to be effectuated to realign the local state. In the context of the conventional grid, this option is always offered implicitly and is exerted continuously—flexibility is administered centrally.

B. *Planning State Adaptation*

Alternatively, the planned schedule could be adapted to reflect the predestined behavior. This means that the anticipated state should be revised. The flexibility for correcting the behavior can be sourced both locally or in the near vicinity, violating the planning of the affected devices. When the flexibility of (a subset of) the local state is exhausted, one must mend this provisionally or perform replanning.

The subtle difference between these two approaches, planning state interception and adaptation, should be observed. The former aims to conserve the state assumed during planning, while the latter aims to conserve planned behavior.

This corresponds to a difference in perspective with respect to attaining objectives. The former has the goal to retain continuity in the long run at the expense of accepting a performance penalty in the present. The latter has the goal to evade actions which immediately detriment the objective while accepting state deviations in the planning.

Based on these characteristics, we expect that the interception approach will be benefited in particular by interactive cooperation, which increases the rescheduling flexibility. The adaptation approach should particularly benefit from replanning, repairing mismatch before it becomes problematic.

C. Planning Defection

At a certain point in time one may, either predictively or instantaneously, observe that the planning is or will become infeasible. A simple strategy to work around such situations is to drop the planning and continue without it for some time, avoiding planning induced problems. The disadvantage is that an unplanned control strategy is needed, which preferentially should be reasonably good. One should ensure that this strategy is not triggered unnecessarily to retain average case characteristics.

D. Predictive Replanning

A planning must be completed before it is brought into effect. Consequently, ample time should be alotted in advance to allow for proper evaluation. While this can be facilely accomplished for scheduled replannings, failure of physics to yield to the forecast can render the current schedule void, demanding reconsideration.

A replanning can be arranged up front when problems are foreseeable (and foreseen), providing opportunity for proper planning. Multiple outcomes may be considered with separate plannings to accommodate uncertainty. Definite commitment to any of these plans can be postponed to the instant of execution.

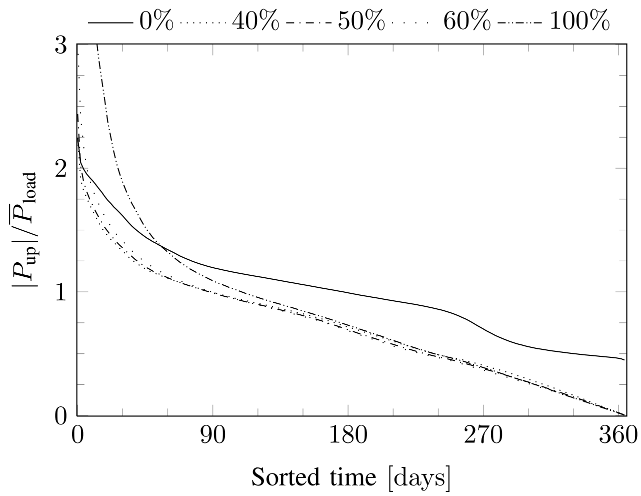
E. Coarse Planning

Failing to anticipate the necessity of diversion in a timely manner, one is forced to invent a substitute swiftly. Before resorting to context-oblivious control approaches, a fall back to rapid planning methods is preferred, presumably at the expense of accuracy. The latter can be made up with subsequent replanning.

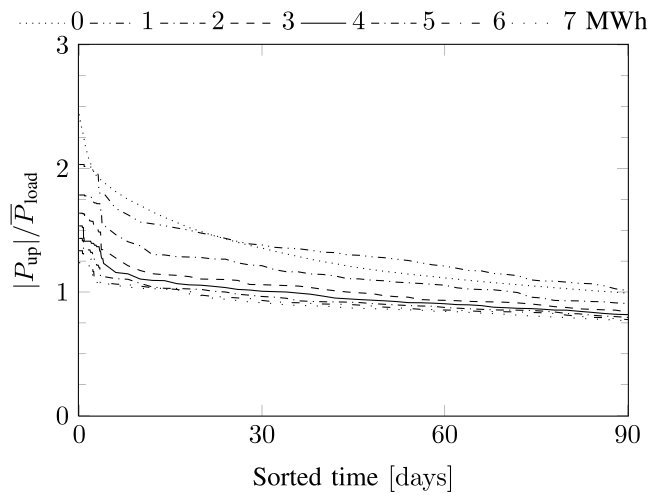
A large part of the provisional planning should never be put to purpose, serving merely to estimate the future behavior and state. Therefore, accuracy of this part can be sacrificed with limited impact. For instance, the temporal granularity may be decreased. As the complexity of solving an optimization problem typically grows superlinearly (and often even exponentially) with problem size, substantial reductions of computational effort can be attained while retaining its principal anticipatory advantage.

V. Renewable Generation Scenario

To demonstrate the potential benefits of adaptivity quantitatively, we demonstrate the problems arising from the use of a representative set of basic adaptation strategies. We do this using a wind production scenario, coupled with a large load and centralized storage.



(a) Transmission load by annual average wind contribution, no storage.



(b) Transmission load by storage dimension, 50% wind contribution, using (near) optimal planning. Only the most significant (worst case) part is shown.

Fig. 3. Load duration curves used to determine system parameters.

A. Scenario Definition

We use measurement data from a wind turbine situated in Germany of 2010, provided by RWE. The generator has a nominal capacity of 1.8 MW and shows an annual yield of 17.1% in this data set.

The grid operator is incentivized to increase efficiency by minimizing transport losses and decreasing the needed medium voltage transmission capacity. To this end, electricity should be consumed locally where and when it is produced. We assume that the wind park is located near to a residential load center with a suitable load dimension. Several wind contribution dimension choices are evaluated in Fig. 3a, demonstrating that wind generation can help reducing the average case load but does not aid in reducing the demand peak load. We choose a 50% annual local wind contribution ($\overline{P}_{\text{wind}} = 307.8$ kW $\rightarrow$ $\overline{P}_{\text{load}} = 615.6$ kW), because this matches the demand and the infeed peak.

Near to the load and the wind turbine, a lossless storage facility is introduced with no transport losses and bounded

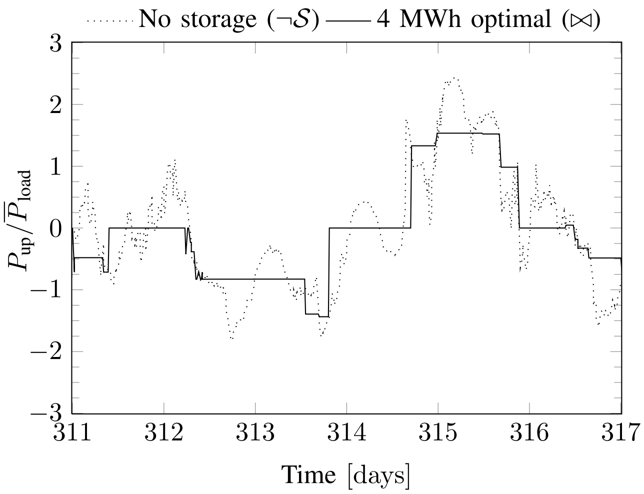


Fig. 4. Load curves under worst case wind supply conditions. Note the 24-hour demand pattern which is visible in '$\neg\mathcal{S}$'.

capacity. The optimization goal is to use the storage to minimize the peak transmission load ($|P_{\text{up}}|$).

More formally, the problem can be stated as follows:

τ	Time interval length := 900 s
n	Number of time intervals := 35040
$\mathcal{T}$	Time interval indexes := $\{0 \dots n-1\}$
$\mathcal{T}'$	$\mathcal{T} \cup \{-1\}$ (initial state)
$\mathcal{H}$	Entities := {wind, load, bat, up}
$\mathcal{H}_s$	Storage entities ($\subseteq \mathcal{H}$) := {bat}
$P_h(t)$	Electricity flow rate to/from $h \in \mathcal{H}$ at $t \in T'$
$\mathcal{S}_h(t)$	State of Charge of $h \in \mathcal{H}_s$ at $t \in \mathcal{T}'$
$\mathcal{S}_h^{\max}$	Maximum State of Charge of $h \in \mathcal{H}_s$
ϵ	$\ll 1$ (improve average-case behavior)

Minimize:

$$\max_{t \in \mathcal{T}} |P_{\text{up}}(t)| + \epsilon \cdot \sum_{t \in \mathcal{T}} |P_{\text{up}}(t)| \tag{1}$$

Subject to:

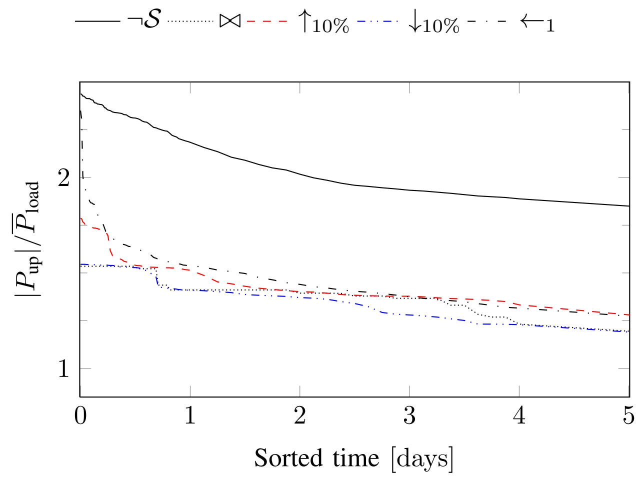
$$\textstyle\sum_{h \in \mathcal{H}} P_h(t) = 0 \qquad \forall t \in \mathcal{T} \tag{2}$$

$$\mathcal{S}_h(t) = \mathcal{S}_h(t-1) + P_h(t-1) \cdot \tau \qquad \forall t, h \in \mathcal{T} \times \mathcal{H}_s \tag{3}$$

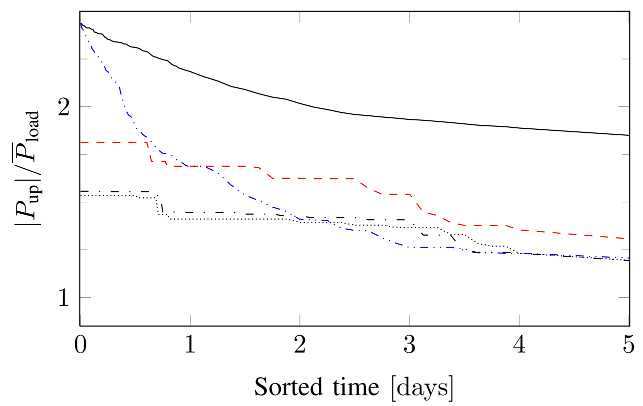
$$0 \leq \mathcal{S}_h(t) \leq \mathcal{S}_h^{\max} \qquad \forall t, h \in \mathcal{T}' \times \mathcal{H}_s \tag{4}$$

Simulations are performed using AIMMS, employing CPLEX for linear programming. As a compromise between computation time and accuracy, an execution window of 48 (12 hours) and a planning window of 192 (2 days) are respectively used. This was found to be 0.13% worse than the full-year optimum for the baseline scenario.

Subsequently, a sensible value for $\mathcal{S}_{\text{bat}}^{\max}$ is determined. Fig. 3b presents the load duration curves under (near) optimal control for several options. The graph suggests $\mathcal{S}_{\text{bat}}^{\max} = 4000$ kWh as a sensible choice, approaching saturation. We observe that the time of the peak remains approximately constant (Fig. 4). Investigation shows that windstorm 'Carmen' caused this peak around November 12th, 2010 [23].



(a) Planning state interception



(b) Planning state adaptation

Fig. 5. Load duration curves per adaptive control strategy under several error models. Note that only the most significant (worst case) part is shown.

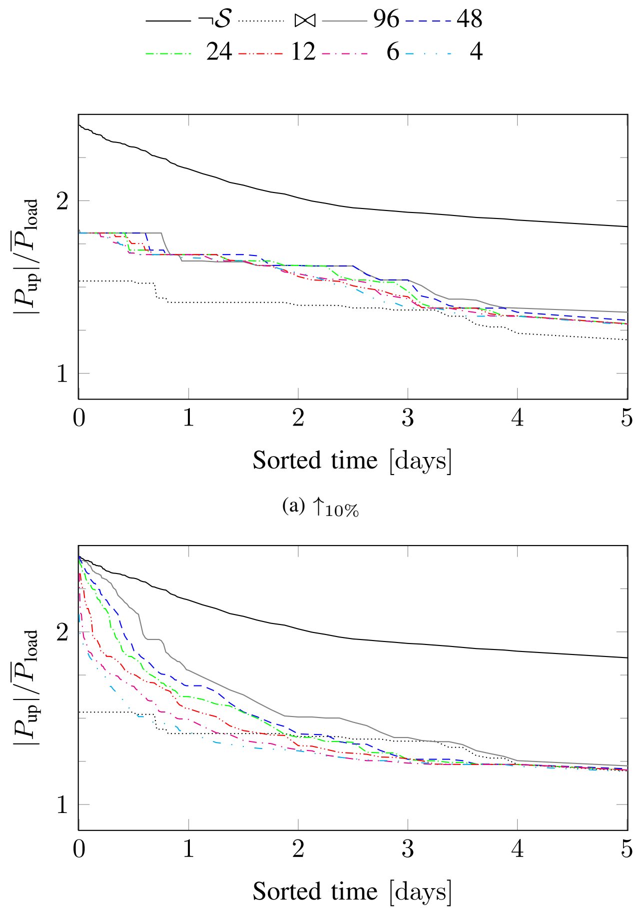
B. Forecast Error Injection

Next, a prediction error is introduced. After planning based on a variant of (1) incorporating the forecast error, the execution window is committed based on the actual profile, using an adaptive policy. We consider the following wind forecast error models: no error ($\bowtie$), the persistence model ($\leftarrow_1$; Section II-A1), relative overestimation ($\uparrow_{x\%}$) and relative underestimation ($\downarrow_{x\%}$). We suppose $x = 10\%$; the mean absolute error of $\leftarrow_1$ in the data set is 9%. For reference, we also show $\mathcal{S}_{\text{bat}} = 0$ (labeled $\neg\mathcal{S}$).

The policies considered are planning state interception and adaptation (Section IV). In this scenario this translates to using transmission and storage to cope with misprediction when possible, respectively. The results are presented in Fig. 5 and will shortly be discussed in more detail.

C. Simulation Results

For planning state interception (Fig. 5a), production overestimation leads to a notable peak increase. The explanation found for this is that the planner underestimates its (negative) peak shaving capability. An even higher peak originates from persistence model forecast errors. Furthermore, these occur at times where there is ample storage capacity left to avoid them.



(a) $\uparrow_{10\%}$

(b) $\downarrow_{10\%}$

Fig. 6. Load duration curves of planning state adaptation for $\uparrow_{10\%}$ and $\downarrow_{10\%}$ by execution window length. Note that only the worst case part is shown.

In this case, this is caused both by unanticipated transitions from near-absent to near-full wind production and vice versa. In the case of production underestimation, peak demand is almost equal to the (near) optimum. For the shown part, performance appears to be slightly better due to an optimization goal definition issue in the ϵ term: it is indifferent to where behavior is improved.

For planning state adaptation (Fig. 5b), both production overestimation and underestimation lead to a substantial increase of the peak upstream load. In both cases, the peak is observed at the upper buffer bound. For overestimation, the buffer is employed to *instantiate* the predicted peak condition. For underestimation, it can be attributed to premature buffer capacity exhaustion. The peak increase resulting from the persistence error model is marginal, because the integral production is forecasted accurately.

The results in Fig. 5b suggest that more frequent replanning may decrease the planning mismatch, which is explored in Fig. 6. These results show that for overestimation, the peak is maintained at small window lengths, because the aforementioned problem persists. For underestimation, buffer state reconsideration substantially improves performance at small window lengths. These are however highly impractical due to computation and communication limitations.

D. Evaluation

We find that a suitably sized residential load can substantially reduce the infeed peaks induced by a wind generator. This is particularly by virtue of its base load (42% of average load over the year and 46% in the week with the worst mismatch in our data set). The converse is not true, as large wind production does not incline to coincide with large demand. In the average case, absolute transmission load reductions are demonstrated to be feasible.

Up to a saturation point, storage can aid substantially to decrease peak load. It must however be observed that proper control is imperative. Improperly controlled storage is shown to be capable of aggravating load peaks.

Forecast errors matter in the worst case and must be accommodated with an appropriate adaptive control strategy. Appropriateness is however error mode dependent. The simulation results clearly suggest a duality between planning state interception and adaptation, accomodating distinct circumstances. To reach a satisfying solution, a balance should be struck between these extremities, meeting both immediate and forthcoming needs.

VI. Conclusion

This work demonstrates that, to exploit the potential of planned smart grid control in a realistic context, the possible impact of forecast errors on grid resources can be of significant order and therefore that forecast errors must be accommodated adequately. We show the following points:

- Planned use of smart grid resources can contribute to a significant reduction in power infrastructure load, both in the peak as well as in the average case.
- Under a realistic forecast error model, these errors affect worst case conditions in particular.
- Control strategies exhibit different error mode behavior, depending on the error model.

However, before this work can effectively be incorporated into TRIANA, several important aspects ought to be accounted for in subsequent work.

A. Future Work

We abstracted from the distributed context in this work, concerning ourselves with transmission rather than distribution problems. Also, several optimistic assumptions have been made regarding the storage resource. These issues should be addressed in the future.

Next to investigating adaptive control policies, the consideration of adaptivity in the planning (cost function) itself should be evaluated, using techniques related to stochastic MPC to manage prediction errors.

In the simulations performed in this work, we assume that it is possible to make a reasonably accurate forecast of the electricity profile. It would be interesting to investigate what happens when this assumption is wrong, and at what point a strategy which does not rely on a prediction exhibits better performance.

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VIII. Biographies

Hermen A. Toersche was born in Westerhaar-Vriezenveensewijk, the Netherlands in 1986. He received his M.Sc. degree in Computer Science from the University of Twente, Enschede, the Netherlands in 2010 at the Computer Architecture for Embedded Systems group, where he currently also is a Ph.D. candidate. His research interests include efficient distributed embedded systems.

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Albert Molderink received his B.Sc. and M.Sc. degree in Computer Science from the University of Twente, Enschede, The Netherlands, in respectively 2004 and 2007. In 2011 he received his Ph.D. degree from the same university. He is working in a research group that investigates the possibilities of increasing energy efficiency using embedded control, mainly via optimization and control algorithms. His research focus is on algorithms to optimize energy streams within a house.

Johann L. Hurink received a Ph.D. degree at the University of Osnabrück (Germany) in 1992 for a thesis on a scheduling problem occurring in the area of public transport. From 1992 until 1998 he has been an assistant professor at the same university working on local search methods and complex scheduling problems. From 1998 until 2005 he has been an assistant professor and from 2005 until 2009 an associated professor in the group Discrete Mathematics and Mathematical Programming at the department of Applied Mathematics at the University of Twente. Since 2009 he is a full professor of the same group.

Current work includes the application of optimization techniques and scheduling models to problems from logistics, health care and within Smart Grids.

Gerard J. M. Smit received his M.Sc. degree in electrical engineering from the University of Twente. He then worked for four years in the research and development laboratory of Océ in Venlo. He finished his Ph.D. thesis entitled "the design of Central Switch communication systems for Multimedia Applications" in 1994. He has been a visiting researcher at the Computer Lab of the Cambridge University in 1994, and a visiting researcher at Lucent Technologies Bell Labs Innovations, New Jersey in 1998. Since 1999 he works in the Chameleon project, which investigates new hardware and software architectures for battery-powered hand-held computers. Currently his interests are: low-power communication, wireless multimedia communication, and reconfigurable architectures for energy reduction. Since 2006 he is full professor in the CAES chair (Computer Architecture for Embedded Systems) at the faculty EEMCS of the University of Twente. Prof. Smit has been and still is responsible of a number of research projects sponsored by the EC, industry and Dutch government in the field of multimedia and reconfigurable systems.