The role of future information in control system design for shipboard power systems

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Synopsis

Both naval and commercial ships are incorporating new power and energy system technologies to improve fuel economy and performance while servicing high power pulsed loads. These assets can be best utilized with load demand forecasting and/or prediction, especially when considering limits on generator ramp rates, distribution lines, and energy storage capacity. Obtaining future load demand data and designing a controller to accommodate it can be challenging, but with potentially large payoff. However, this information is not useful in all cases. This paper develops a method to quantify the potential value of future information depending on the specific power system characteristics. This quantitative approach aids designers in deciding how and when to deploy future forecasting in controller design, and provides insight into the potential benefits of these more complex controllers. To quantify this trade off, two optimization-based control methods are developed. One uses only current information, while the other has an exact forecast of the future. As examples, the method is applied to a notional naval ship and drill platform service vessel with representative power and energy system architectures under indicative operational load demands.

Keywords: Power System Design; Predictive Control; Energy Storage; Dynamic Loads

1 Introduction

New technologies are being deployed in marine power systems including batteries, fuel cells, integrated electric propulsion, and standby generators. These systems can improve fuel economy and performance, and service more exotic loads. Many of these system elements are time dependent and their current state depends on past actions, like stored energy or fuel cells with slow power ramp rates. Even traditional generators have finite ramp rates that cannot serve some modern pulse-power loads.

Traditionally, power systems could be analysed in steady state to determine if the generation was sufficient to meet loads, but as the system elements become time dependent they become much more difficult to analyse and control Zivi (2002); Monti et al. (2005). This control is critical to realizing the benefits of the new components Kankanala et al. (2012); Hossain and Ginn (2017); Hou et al. (2018). For example, energy storage devices should be charged in anticipation of large loads Chan et al. (2011); Bernardes et al. (2003); Im et al. (2016); , and standby generators should be started in advance. Rapid decreases in load can be equally problematic. Numerous proposed control architectures explicitly consider the system dynamics.

When discussing control of these dynamic systems, for clarity we use the terminology of "predictions" and "forecasts." The generation system dynamics can be modeled, so it is often possible to predict the future system state based on the control inputs - the known system commands determined by the controller. The un-modeled changes are considered disturbances to the system and often arise from changing loads. This is the general form of model predictive control (MPC) in which a plant model is used to predict the effects of possible control actions over a fixed time horizon. In MPC, the controller selects the best input choice, applies that command at the current time step, and repeats the process at the next time step. There are both linear and nonlinear versions Zohrabi and Abdelwahed (2017); Zhu et al. (2017); Vu et al. (2015); Haseltalab and Negenborn (2017) and they can be centralized or distributed Banaei and Alizadeh (2016). These controllers set the power levels of the various generators, sometimes curtail loads, and can be used for system breaker configuration Zohrabi et al. (2017). In all of these works, the controller does not have advanced knowledge of changes in load, but it can predict the results of its own actions on the plant.

By contrast, a forecast is an estimate of future disturbances that the controller cannot change, but may have some knowledge of. For more aggressive and rapidly changing loads, the controller may receive a forecast of future loads to better prepare for fast transients Gonsoulin et al. (2017); Vu et al. (2017); Stone et al. (2015); Park et al. (2015). The controller then incorporates this forecast as it makes its predictions for the effects of the control actions. This type of control is also typically called MPC.

This paper considers the control and analysis challenges of using time-dependent power system elements and the relative importance of future forecasts to mission success. In some cases this future information is critical, while in other cases it provides no benefit. Specifically, even if a controller uses a prediction model like MPC, it has no explicit future forecast and could be compared with a more typical PID or other standard controller. Adding an explicit future load forecast is often difficult and inaccurate, so it is useful to quantify the potential benefits of this approach. For example, future load information is critical to a drill platform servicing a vessel attempting to temporarily shut down engines, while the information is irrelevant when the ship is at steady state cruise. Naval vessels servicing rapid pulse loads also benefit from forecasts.

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To quantify this difference, this paper compares the unserved load with and without future knowledge. Power systems require some form of controller Paran et al. (2015); Vu et al. (2017), but rather than design a controller for every case an optimization process is used that mimics the behaviour of an ideal controller. Herein, two types of optimization methods are used to generate controller behavior. The first optimization algorithm is described as an "instantaneous" controller because it only has knowledge at the present time. The second algorithm is called a "multi-period" controller because it has exact future knowledge of load demands, which essentially can consider many actions at many different times. Practically speaking, the tradeoff between the two methods is the value of future knowledge at an additional computational cost. The multi-period controller is very difficult to fully implement in practice as it assumes exact future knowledge on a long horizion, but it provides an upper bound on the system performance given a specific system architecture. These two controller types have been proposed separately before, where the instantaneous version was discussed in Chan et al. (2009); Cramer et al. (2013, 2015) and the multi-period version was shown in Oh et al. (2017). The goal here is to compare the two and rigorously quantify the value of the forecasts for different architectures and operating conditions.

When using MPC, the advanced knowledge given to the controller depends on the application and it is a design decision. The multi-period controller in this paper has exact future knowledge for the whole simulation horizon, so a more practical controller like MPC with a limited lookahead capability should exhibit performance somewhere between the instantaneous and multi-period optimizations. As the MPC horizon gets longer its performance should approach the ideal multi-period case assuming the forecast is accurate.

The sections that follow first present some limited conditions when future forecasts are not useful, then develops the two control methods for comparison. The ship architectures are then described, followed by results and conclusions.

2 Analysis

Providing sufficient overall power for dynamic load demands is a primary consideration in ship power system design and the focus of this paper. Fuel economy is not directly studied, but it does have a strong secondary effect in that correct system control can allow generation assets to be turned off rather than left idling.

This section first proposes some simple conditions to quantify when future information is not useful, and then establishes that even minor system complexity requires more advanced analysis to understand the value of a forecast. The instantaneous and multi-period optimization based control algorithms are then described.

2.1 Relevant operating conditions

Load shortfalls can occur when power ramp rates exceed capacity, if there is insufficient total generation, or transmission bottlenecks. Power plant lineups are often optimized for fuel economy, which implies that offline generators will need time to start up in order to serve the maximum load. To formulate the problem, each generator i has maximum and minimum power limits such that

$$p^i_{min} \leq p^i_{gen} \leq p^i_{max}. \tag{1}$$

Both gas turbine and diesel generators have positive and negative rate limits r^i_+ and r^i_- that are significantly less than ramp rates of newer system loads. Assuming these ramp rates do not depend on operating condition, they can be defined as

$$r^i_- \leq \frac{p^i_{gen,t} - p^i_{gen,t-1}}{\Delta t} \leq r^i_+ \tag{2}$$

where $p^i_{gen,t}$ and $p^i_{gen,t-1}$ represent the i^{th} generator power at time t and $t-1$.

The total generation capacity is simple to check, but ramp rates require more analysis to account for the dynamics involved. If we assume n generators have identical ramp rates and capacities, and share power equally, then the total system ramp rates are nr^i_- and nr^i_+ across the full range from zero to full system capacity. If the load ramp rate stays within these bounds, the system is able to provide sufficient power even without future predictions, and there is little benefit in a multi-period controller with forecasts. However, if the generators differ in either their specifications or operating conditions, then more detailed analysis is required. For example, one generator may hit its maximum power limit before the others and thus be unable to contribute to total system ramp rate. Operating points selected to minimize fuel consumption are often not ideal for response to fast load ramp rates.

Even analyzing the startup of idle generators requires significant simplification. Let us assume an offline generator requires some time to start, synchronize, and come online at zero load. It can then respond to a load based on its ramp rate. A simplistic analysis might assume that now with $n+1$ generators, the ramp rate capacity is $(n+1)r^i_+$. However, even if the next generator is assumed to be online before the existing generators reach capacity, this condition is not sufficient because the existing generators no longer contribute to the power ramp once they reach their maximum.

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These dynamic factors drive the need for automated methods to analyze and control the power system, even without the addition of energy storage.

2.2 Energy storage models

Energy storage devices like batteries, capacitors, and flywheels can be added to provide additional power capability. The energy available in the energy storage system evolves over time and the units cannot provide sustainable power, so constraints are added to reflect their storage capacity. We use a relatively simple model for energy storage that is agnostic to the storage technology or hybrids thereof and provides bidirectional power flow.

Each energy storage unit has a maximum and a minimum power limit (e.g. $\pm$ 10 MW) and an energy capacity (e.g. 60 MJ). The storage is approximated as lossless, so the power output is integrated to determine the energy storage state,

$$E_{min} \le E_{start} - \sum_{t=0}^{\tau} p_{es_i}(t)\Delta t \le E_{max} \quad \forall \tau \in \{0, ..., T\} \tag{3}$$

where $p_{es_i}(t)$ is power from the energy storage i (positive for output power), Δt is time step, and E_{min} and E_{max} are minimum and maximum energy capacities, respectively. Example capacity ranges can be 0–60 MJ with 30 MJ starting point, or equivalently $\pm$ 30 MJ with a 0 MJ start. In reality, there is some energy lost in the charge and discharge process, but this is neglected here to consider overall power availability rather than efficiency.

2.3 Optimization-based analysis

To study the relative value of this future information, two control methods are used. One considers only current information, and the other has full future knowledge. Many methods exist to mathematically formulate the problem, for example linear vs nonlinear models, and whether decision variables should be generator powers or line flows. This section focuses on the overall optimization goals rather than the details of the numerical solution.

2.3.1 Instantaneous optimization

The general form for an instantaneous single-period optimization is a minimization of some cost function subject to constraints defined as

$$\min_{p_g, p_{es}} c_{gen}(p_g) + c_{es}(p_{es}) + c_z(p_g, p_{es}) \tag{4}$$

such that

$$g(p_g, p_{es}) = 0 \tag{5}$$

$$h(p_g, p_{es}) \le 0 \tag{6}$$

$$p_{min} \le p_{gen} \le p_{max} \tag{7}$$

$$p_{es_{min}} \le p_{es} \le p_{es_{max}} \tag{8}$$

$$l \le A \begin{bmatrix} p_g \\ p_{es} \end{bmatrix} \le u. \tag{9}$$

The basic costs are associated with generator c_{gen} and energy storage usage c_{es}. The functions g and h represent equality and inequality constraints on the system like power flow and line limits. The generic cost function c_z includes any other design attributes like a desire for generator balancing. Some portion of the problem may be linear, and those constraints are often represented separately in (9) to simplify the solution. This setup is generic and admits a variety of optimization setups from linearized DC systems with direct control of line flows to full nonlinear AC power flow equations. With some simplifying assumptions, the problem can become a linear programming problem. More details of the actual numerical solution method used here are available in Cramer et al. (2013, 2015).

2.3.2 Multi-period optimization

The multi-period control optimizes power and energy management for the entire scenario at once by assuming perfect knowledge of all loads. It simultaneously considers past, present, and future demand at all times. This is distinctly different than a single-period controller, which optimizes commands only at each time step.

Conceptually, the optimization simultaneously analyzes copies of the power system at each of T time steps. The decision variables p_g, p_{es} have a representation at each time step that combine to create the extended multi-period decision variables $\bar{p}_g = \{p_g(1), p_g(2), ...p_g(T)\}$, and $\bar{p}_{es} = \{p_{es}(1), p_{es}(2), ...p_{es}(T)\}$. For a power architecture with n_g generators and n_{es} ES, the new decision variables $\bar{p}_g, \bar{p}_{es}$ now have $n_g T$ and $n_{es} T$ and elements, respectively.

After adding the multi-period constraints on energy storage capacity and ramp rates, the final formulation for multi-period optimal power flow is modified from (4) as

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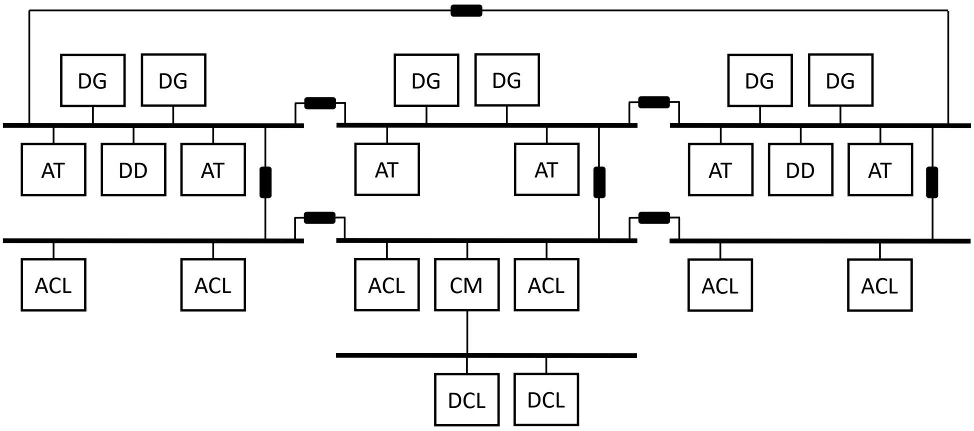

Figure 1: Notional drilling vessel power system as described in Anvari-Moghaddam et al. (2016). DG signifies diesel generator, AT signifies Azimuth Thruster Load, DD signifies Drilling Drive, CM signifies converter, ACL signifies general AC Load, and DCL signifies general DC Load.

$$\min_{\bar{p_g},\bar{p_{es}}} \bar{c}_{gen}(\bar{p_g}) + \bar{c}_{es}(\bar{p}_{es}) + \bar{c}_z(\bar{p}_g, \bar{p}_{es})) \tag{10}$$

where the bar on top of variables include vectors of entire multi-period as suppose to a single-period. The constraints are similarly modified with the extended decision variables. Solution details are available in Oh et al. (2017).

3 Ship architectures

To illustrate this phenomenon, consider two applications: a drill support ship and a naval vessel, both with high power dynamic loads and multiple generators. The naval vessel also has energy storage. The drill ship power system shown in Figure 1 does not contain energy storage or significant transmission constraints and is less complex, so it will be considered first.

3.1 Drill support ship

We consider the architecture studied in Anvari-Moghaddam et al. (2016) with the energy storage element removed, shown in Figure 1. The drill ship has 6 generators with a maximum power of 7 MW each. The analysis considers two cases, one where all the generators have slow ramp limits of 0.117 MW/s (1 p.u./min), and the second where three of the generators are replaced with faster versions with 1 MW/s ramp rates.

3.2 Naval vessel

The naval vessel under consideration is shown in Figure 2. The system has 82 MW of installed generation that can absorb a step load change of 22.2 MW and has a response time constant of approximately 2.9 s. The maximum propulsion load is 60.4 MW. Distributed through the four zones is a total of 3.4 MW of non-vital load and 3.7 MW of vital load. The radar load is 3.8 MW. There are three mission loads. In zone 1, there is a 13-MW mission load and accompanying 13-MW, 780-MJ energy storage. In zone 2, there is a 5-MW mission load and accompanying 5-MW, 50-MJ energy storage. In zone 3, there is a 7-MW mission load and accompanying 7-MW, 420-MJ energy storage.

4 Simulation results

In this section, we present the simulation results for the two different ships under various load demands during representative operational missions.

4.1 Drill support ship

The drill support ship load profile is a simple combination of two steps from 50% to 100% of rated total generation (21 - 42 MW). The first step occurs slowly at positive and negative ramp rates of 0.6 MW/s. The second step is more rapid with a rate of 3.3 MW/s.

The energy storage units are not used in the drill ship model to provide simple examples when future forecasting is not helpful. Forecasts are almost always helpful when energy storage is included.

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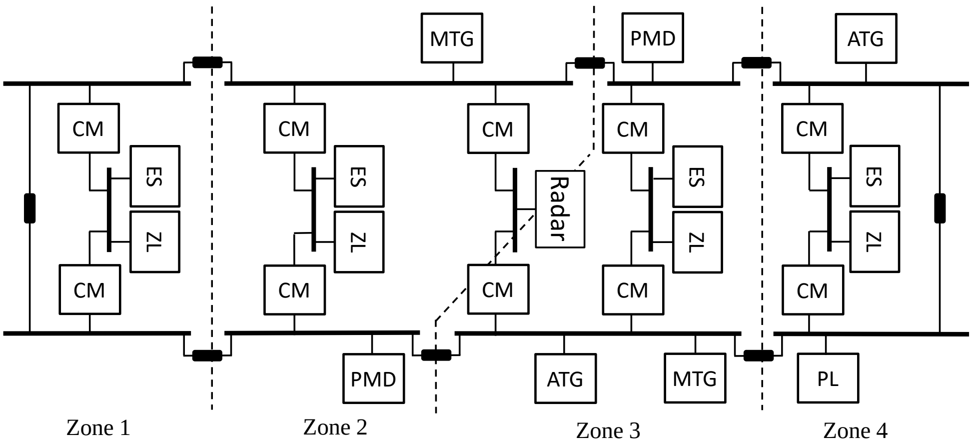

Figure 2: Notional shipboard MVDC system. MTG signifies main generator, ATG signifies auxiliary generator, PMD signifies propulsion, CM signifies converter, R signifies radar, and ZL signifies zonal load.

4.1.1 All slow generators

The drill ship is first studied assuming all the generators have slow ramp rates of 0.117 MW/s, for a total ramp rate of up to 0.7 MW/s. With these rates, the first step load is within the generator ramp rate limits, but the second load step exceeds the total ramp limits. The results are shown in Figure 3 for both the instantaneous and multi-period optimization. The generator power plots also show the maximum and minimum generator power at the time step based on the operating point at the previous time step (1s in the past) to indicate the available ramp capability. If the load power trace is coincident with one of the limits, it means that either the ramp rate of max power constraints are active.

The generators have identical power ratings and ramp limits but slightly different costs, so they do not share power equally but their operating points are very similar. The maximum generator power is sufficient to serve the load, and the first step ramp rates are within the system capability. This satisfies the assumptions of Section 2.1, so we should expect that future forecasts do not help and the instantaneous and multi-period control should yield similar results. This can be seen in the first load step from 25–125 s when both control methods generally serve the load during transients. However, the instantaneous version has a slight power shortfall as it reaches a peak at 70 s. This occurs because the generator operating points are different. Generators 4–6 start at a higher power point than the others, and thus saturate sooner leaving only 3 generators to provide the ramp rate during the end of the ramp from 60-70 s.

During the second power step increase at 150 s, the ramp rate exceeds the installed capacity. It is physically impossible to serve the load, and both controller types fail.

4.1.2 Half fast, half slow generators

The drill ship is next studied assuming three of the generators are replaced with faster versions with 1 MW/s ramp rates. This means the total ramp rate is 3.3 MW/s when no generators are saturated, derived from 3×1 MW/s + 3×0.167 MW/s. With these rates, both load steps are within the total ramp limits, but only with no saturation. The results are shown in Figure 4 for both the instantaneous and multi-period optimization. With different generator ratings, one of the assumptions of Section 2.1 is clearly violated and it is possible that forecasts may help.

The second load step is a change of 21 MW which represents the full capacity of the 3 fast generators, meaning they are likely to saturate. The multi-period control successfully tracks the fast ramp at 150 s by changing the generator operating points in anticipation of the ramp. The load is transferred to the slow generators (1–3) so that the fast generators can operate lightly loaded and be ready to provide the fast ramping power to track the step. The instantaneous optimization does not show this characteristic. The fast generators start at about 50% load and quickly saturate, meaning the load is under-served.

4.2 Naval vessel

To present a second example of these algorithms in action, consider the naval vessel described in Section 3.2. A method to develop load demand scenarios was presented in Stevens et al. (2015). As an example scenario the system is initially operating with partially charged energy storage, cruising at 20 knots, and radar and mission loads off. At 30 s, speed is reduced to 10 knots, and the mission load in zone 1 (13 MW) is turned on. At 75 s, the radar (3.8 MW) is turned on. At 100 s, speed is increased to 20 knots, and the mission load is turned off. At 135 s,

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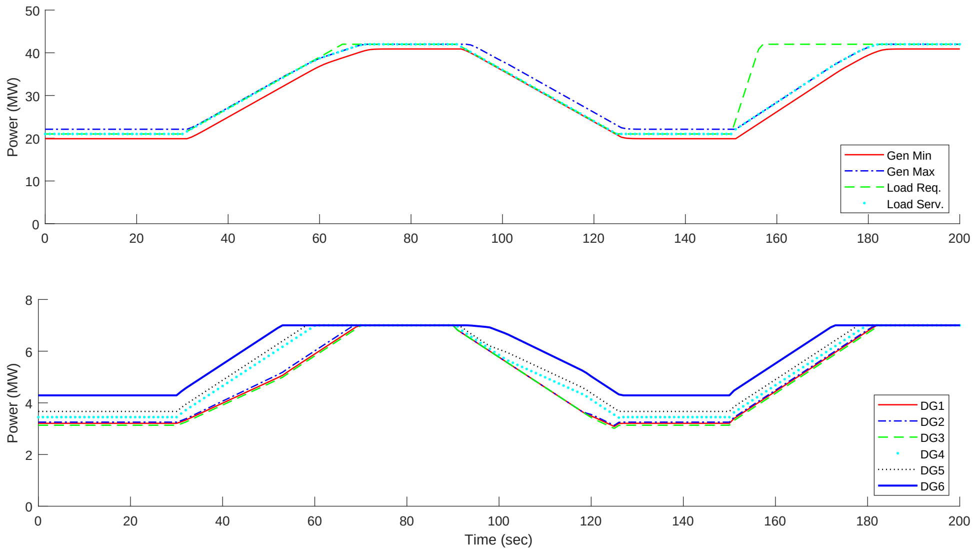
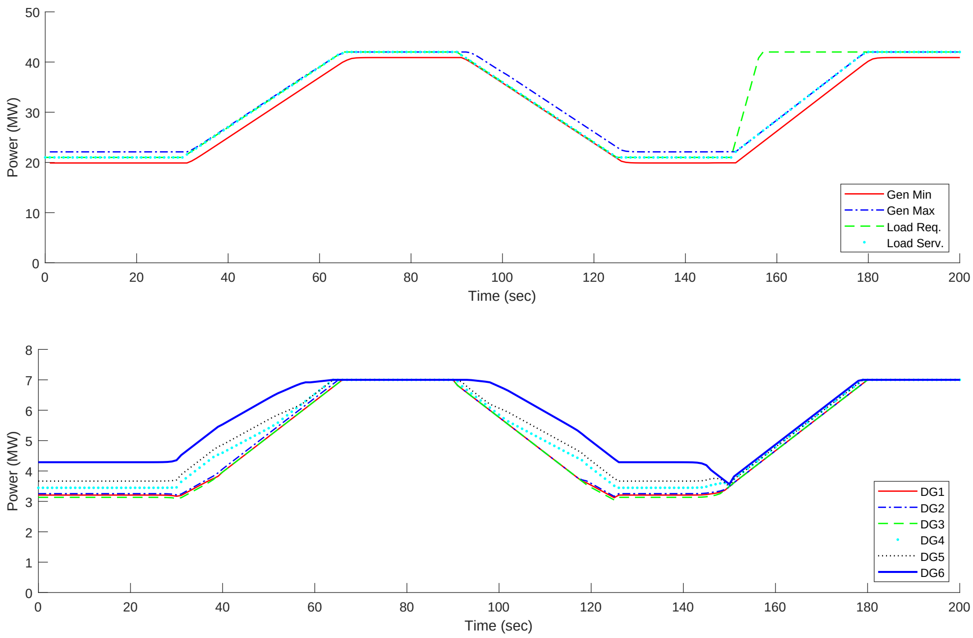


(a) Instantaneous control based only on information at the current timestep.



(b) Multi-period control with perfect future information.

Figure 3: Response to load steps for the drill ship with all slow generators. The ship has six 7 MW generators with identical ramp rates of 0.117 MW/s, for a total ramp rate of up to 0.7 MW/s. The top subplots show the total generation, load, and the maximum and minimum generator power at the next time step (1s). For this configuration that change is ± 7 MW when no generators are saturated. The bottom subplots show the response of the individual generators. Both the instantaneous and multi-period algorithms exhibit similar performance in that they can track the slow ramps, but not the fast ramping at 150s. The generators are physically unable to track this 3.3 MW/s ramp rate regardless of control method, even with perfect future knowledge.

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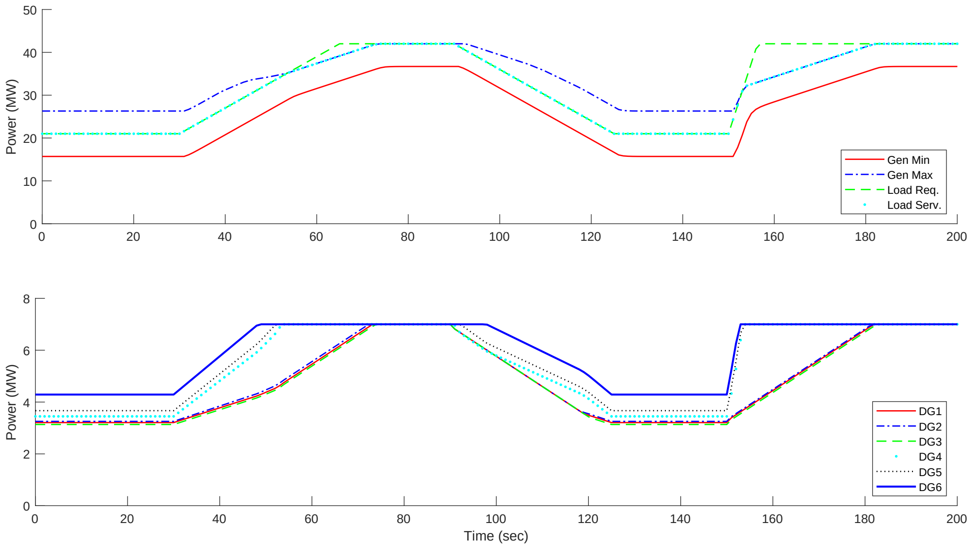
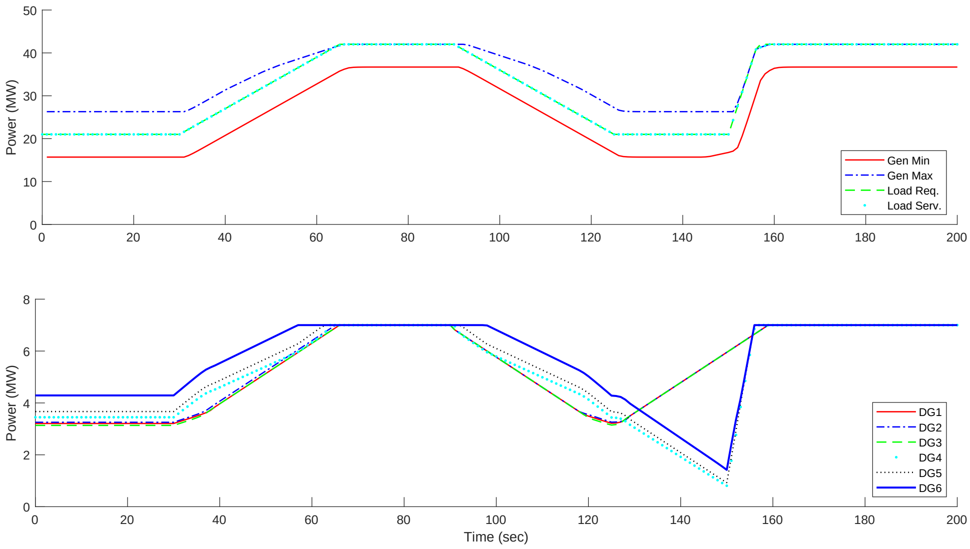


(a) Instantaneous control. The generators are unable to serve the fast load ramp at 150s. The fast generators ramp to track the load, but quickly saturate because they were operating at part load. The slow generators ramp up as well, but this leaves a shortfall from 160–180s.



(b) Multi-period control with perfect future information. Load is shifted from the fast to the slow generators starting at 130s so that the fast generators can track the load ramp at 150s without staturating.

Figure 4: Response to load steps for the drill ship with half fast, half slow generators. The ship has six 7 MW generators with DG 1–3 having ramp rates of 0.117 MW/s, while DG 4–6 have a faster ramp rate of 1 MW/s. The top subplots show the total generation and load, while the bottom ones show the response of the individual generators. The load demand is identical to that in 3. The generators are now physically capable of serving the fast load step at 150s, but it requires pre-planning which is only conducted by the multi-period algorithm. Thus the multi-period algorithm shows much better performance than the instantaneous algorithm.

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speed is increased to 30 knots. The vignette ends at 180 s. For this mission, the performance of the single-period instantaneous optimization method is shown in Figure 5. The same mission using the multi-period optimization is shown in Figure 6.

The power system behavior is significantly more complicated. The loads have different service priorities for preferential load shedding, while the loads are treated equally in the drill support vessel analysis. Individual loads are each shown with their demanded and served power. When the two do not match it indicates the quantity of load shedding required. A second complicating factor is limited power transmission and conversion. The generators, loads, and storage are attached to various locations in the system of Figure 2. The various lines and converters that interconnect them have finite capacity, so there can be a localized shortfall even if there is overall sufficient generation. The control decisions must consider not only the power commands in time, but also with regard to their network location.

The general summary of this scenario is that the ship has sufficient overall generation to serve the load, but a large mission load is installed in zone 1 as part of the zonal load ZL in Figure 6. When this load activates from 30–100 s, it creates shortfalls within that zone, even though other loads have sufficient power.

4.2.1 Instantaneous

Consider the instantaneous case shown in Figure 5. Throughout the scenario, the propulsion and radar loads are fully served because the ship has excess generation and no transmission constraints where these loads are located. This is shown in the "Major" and "Minor" load plots. The other loads have interruptions due to a localized capacity constraint in zone 1. As seen in the top left, the total load demand is fully served except from 30–100 s when the mission load is on. The generation does not exactly match the load because the excess goes to energy storage. The system is also not fully able to match the fast propulsion demand ramp at 135s.

The "Major" and "Minor" loads are all served up to 30 s as seen in the middle plots. The energy storage ES1 in zone 1 is charging, but it is limited by the converter power from the main bus. As shown in the bottom left plot, the converters in zone 1 are operating at full saturated capacity. At 30 s time, the propulsion demand drops and the mission load increases. The zone 1 converters are saturated so the ES1 storage starts draining to supply the load, but it only has limited power capacity and the zone 1 non-vital loads are dropped as shown in the "Minor Loads" plot. The energy storage also has limited energy capacity which depletes at 67 s, when the zone 1 vital loads are also dropped. The Mission load has priority, but it now can only be supplied by the in-zone converters. Note that the other zonal loads are not impacted.

Once the mission load shuts off, the vital and non-vital loads are resumed and the energy storage begins to charge again, although still limited by the zone 1 converter capacity.

4.2.2 Multi-period

Now consider the multi-period controller shown in Figure 6. Many similarities exist, specifically the radar and propulsion loads are served throughout the scenario. However, the multi-period controller does a better job supplying the high priority mission load. In contrast to the instantaneous controller, it immediately sheds both vital and non-vital loads in zone 1 to use the maximum converter capacity to aggressively charge the energy storage in zone 1. This creates more available total energy for the mission load. It also creates a uniform load shedding for the mission load rather than a full power period with a sharp cutoff. This is due to the cost function, which has increasing penalties for larger load shedding. The other zones are unaffected. The recovery period is similar; once the mission load turns off, all loads are restored. The optimization maximizes a weighted load service shown in the bottom right plot. The instantaneous controller of Figure 5 serves all requested load until time 67 s when it has a major shortfall. In contrast, the multi-period controller can predict the load shortfall created by the large mission load, and curtails load ahead of time in order to mitigate the drastic load increase.

5 Discussion

As expected, future information becomes more valuable for systems with time dependent features. Forecasts do not help in some limited conditions, but as shown in the earlier examples even a set of conventional generators can benefit if they do not have identical power limits, ramp rates, and operating conditions. Aggressive loads combined with limited generator ramp rates and startup time is a typical example of a system that can benefit from forecasts. Adding Energy storage to the power system can provide performance benefits, but the control of these devices significantly improves with future forecasting. This implies that systems without forecasting may not realize the full benefits of the storage devices.

The naval vessel example also highlighted the use of forecasts in the presence of transmission constraints. Loads, generators, and storage can be scheduled not just in time but also in location.

The difference in performance between the instantaneous and multi-period controllers provides the quantifiable benefit of future forecasts. However, this metric must be evaluated with caution as it represents a hard upper bound

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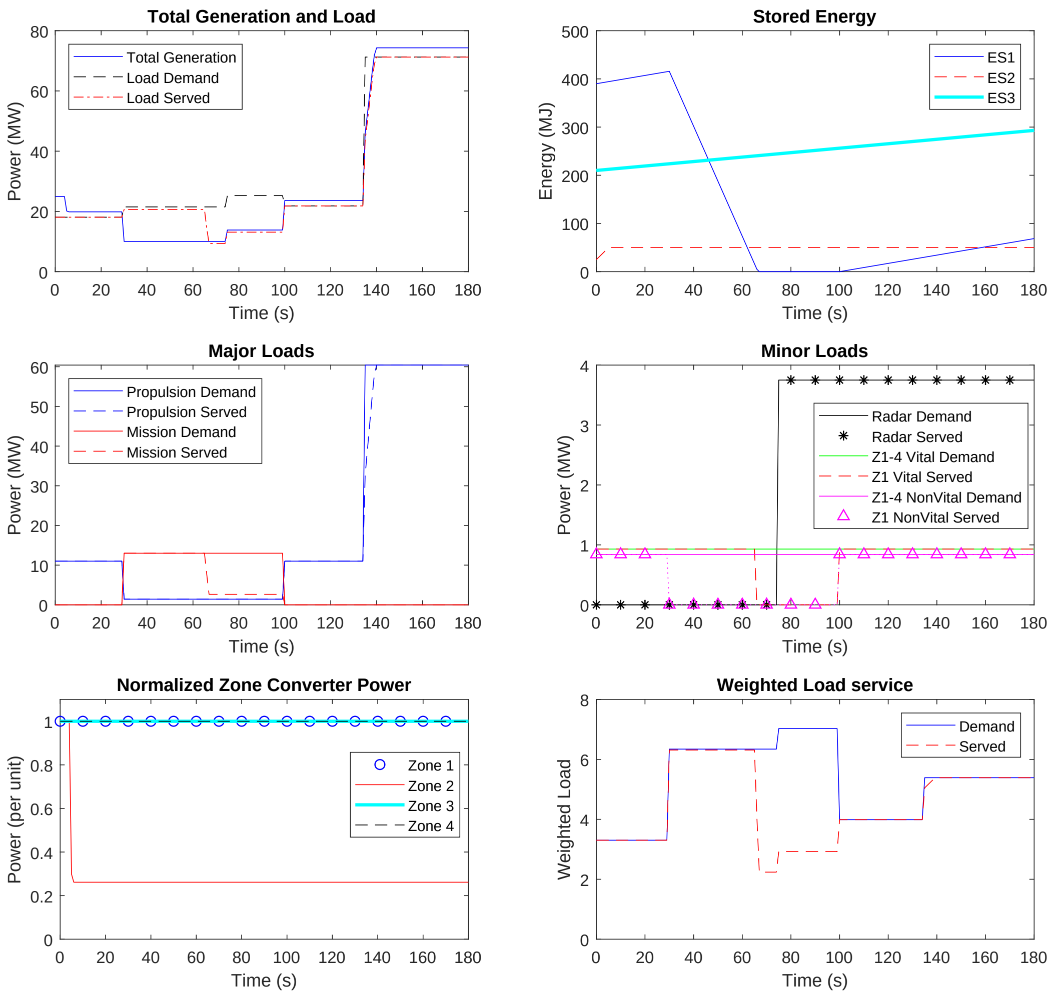

Figure 5: Instantaneous control of the naval vessel. The total load demand is served, except for the period for 67-100s when there is a load shortfall as seen in the top left plot. Total generation and total load do not match exactly due to energy storage usage. Individual load demand and use are shown in the middle plots. The vital and non-vital loads in zones 2-4 are fully served, but the zone 1 loads are shed to service the high priority mission load in zone 1. The normalized converter power in each zone is shown in the bottom left. Zones 1 and 4 are fully utilized the entire period. The converters limit the total power moved into zone 1, so the energy storage ES1 cannot fully charge, nor the loads be fully serviced even though there is sufficient total generation. The loads each have different priorities, so the weighted total load used as optimization objective is shown in the bottom right.

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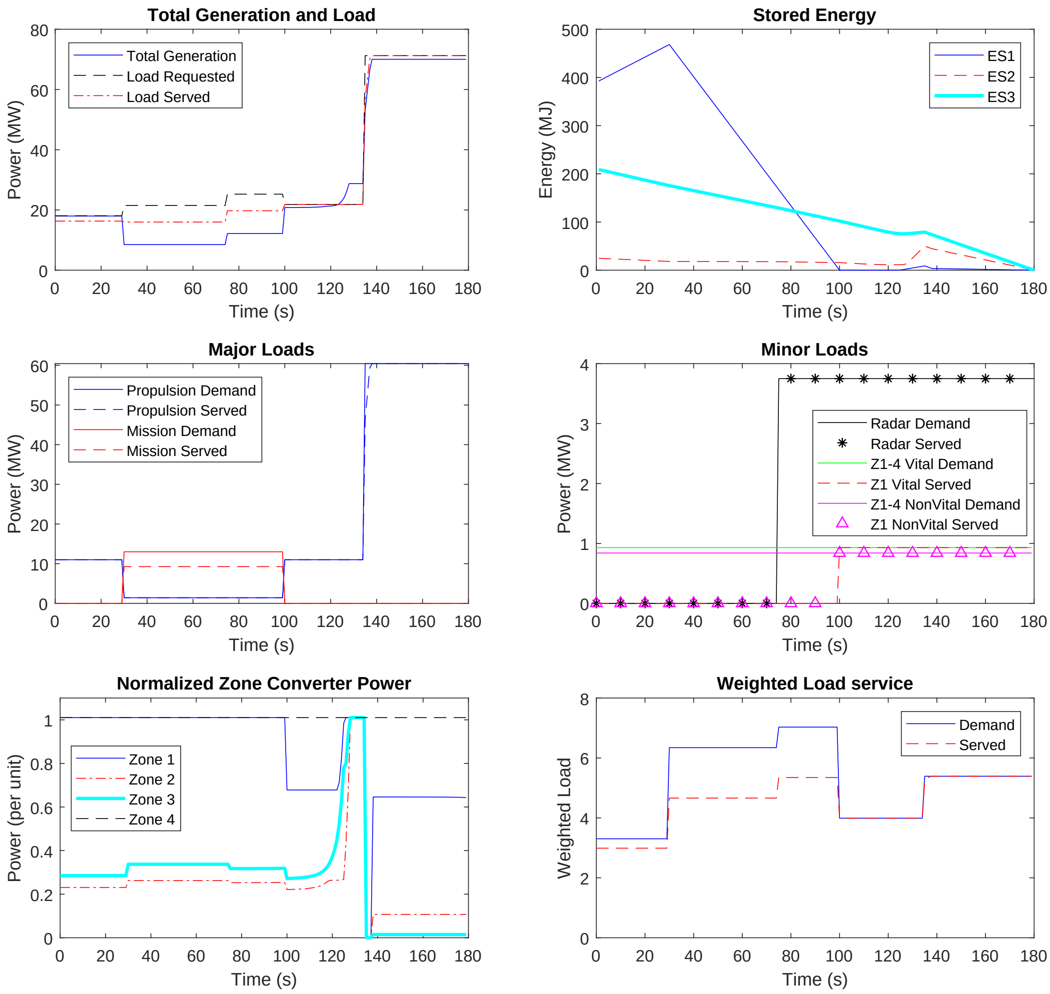

Figure 6: Multi-period control of the naval vessel. The total load demand is served after 100 s, but there are load shortfalls before that time. In contrast to the instantaneous case, the zone 1 loads are shed immediately at time 0 s to fully charge the energy storage in preparation for the pulse from 30-100 s. The load shortfall from 67-100 s is less than the instantaneous case, which comes at a cost of a minor load shortfall leading up to that event.. Total generation and total load do not match exactly due to energy storage usage. Individual load demand and use are shown in the middle plots. The vital and non-vital loads in zones 2-4 are fully served, but the zone 1 loads are immediately shed to better charge the energy storage and service the high priority mission load in zone 1. The normalized converter power in each zone is shown in the bottom left. The loads each have different priorities, so the weighted total load used as optimization objective is shown in the bottom right.

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on that performance. If the future forecast or the dynamic models are incorrect, that maximum performance will not be achieved and the controller may actually do worse than one without forecasting. As designers contemplate a new power system architecture, the methods in this paper can be used to predict the potential performance of different controller classes and evaluate the potential benefits of future forecasting.

6 Conclusions

Modern marine power systems increasingly incorporate new technologies and service fast ramping loads with pulse power demands. The time-dependent nature of these systems indicate that they can benefit from forecasts of future load demand, but implementing such a system is difficult. This paper presents a method to quantify the benefit of this future information. Some power systems may see no value in future forecasting, but systems with load ramp rates approaching generator limits or those with energy storage generally benefit. Transmission or power conversion limits introduce additional location-based complexity in the problem that can be addressed with forecasts.

Two optimization based controllers were developed, one with only current instantaneous information, and the other with full future knowledge of load. Each represents an upper-bound performance given the information available, so the difference between the two reflects the value of that information. Implementing a real controller with exact load forecasts is very difficult, but the methods here allow a rigorous quantification of the potential benefits to determine if such an idea is worth pursuing.

These ideas were demonstrated on a drill platform service vessel with both slow- and fast-ramping generator lineups, and on a naval vessel with electric propulsion, transmission and conversion constraints, and demanding mission loads. Future information was shown to have potentially large or small benefit depending on the architecture and the operational scenario. This analysis technique can be used to quantify the benefits of potential control strategies and forecasting techniques early in the design phase.

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