Battery Storage Control for Steadying Renewable Power Generation

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Abstract

We consider two methods for managing fluctuations in power generation due to intermittent renewable energy generation. Excess energy must be stored during times of excess power generation, and then released when power generation decreases, thereby stabilizing the energy supply. We will consider evening the supply by storing excess power to a battery during excess generation, and then releasing the energy when power generation diminishes. Among other considerations, we would like to release and store energy at a bounded rate, and restrict the power saved (thereby reducing the required battery size).

1 Introduction

There is an international push to increase our use of clean, renewable electric energy. Many states within the United States have adopted renewable portfolio standards, which require a certain percentage of electric energy production to come from renewable resources. In the 2011 State of the Union Address, President Obama stated that he wants the USA to have 80

These mandates pose new technical challenges to operating the high-voltage electric grid. Much of the renewable energy requirements will come from future investments in wind energy and solar energy. Solar energy and wind energy are not controllable generation resources like traditional generation resources such as coal, natural gas, nuclear, and hydro. These resources are intermittent and can have fast and unpredictable output fluctuations. These fluctuations pose a strain on the operations of the grid. For instance, grid operators must have backup generation on standby in order to compensate for the intermittency of these resources.

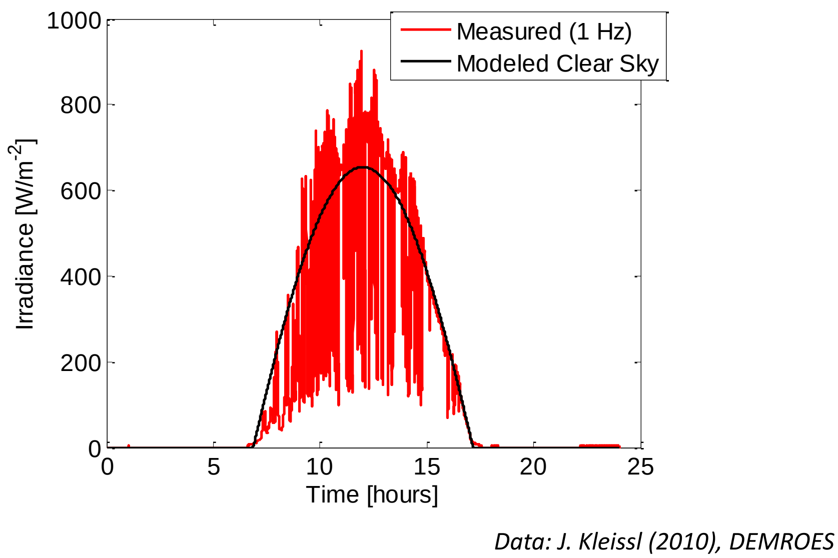

Figure 1: True Output (Red) Vs. Clear Output (Black) with no clouds, etc.

As an example of renewable generation intermittency, consider Figure 1. It demonstrates the variation of power output from a solar panel. The red curve demonstrates true measured power output. The black curve demonstrates the expected output with no noise (i.e., constant sun over the course of a day with no clouds, birds, or other objects passing over the panel, etc.). The red curve demonstrates the sharp noisy variations produced by real solar panels which can be disruptive to the grid, and can be smoothed via battery storage. Note that solar panels which are located closely to one another will have highly correlated power noise. Thus, one can not hope for noise variations from many panels to average out the noise too much.

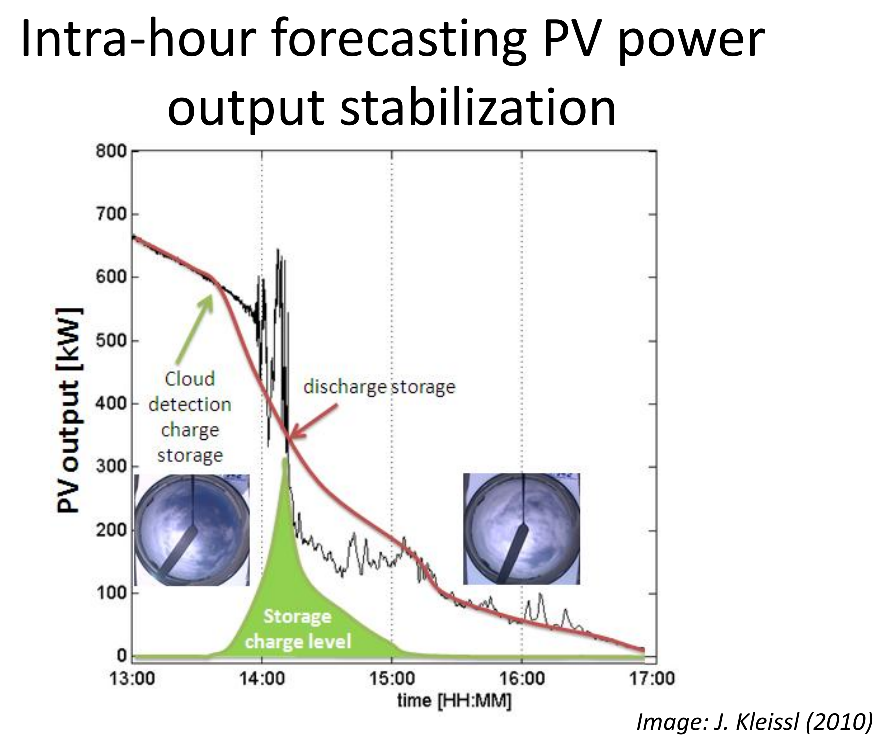

Figure 2: Battery Used to Level Power Output from Solar Panel

One technique to limit the impact of these intermittent resources on the grid is to couple them with energy storage, i.e., a battery. For instance, when a cloud passes over a solar panel, the output of energy can drop by 70% very quickly. A battery can be used to smooth out this fast drop in electric energy to the grid such that the net output to the grid has a much slower rate of change. See Figure 2 for an example of a solar panel/battery unit. This type of system is exactly what we will consider optimizing in this report.

The remainder of this report is organized as follows: In Section 2 a linear programming model is considered for optimizing both the required battery storage size, and battery charge rates. Minimizing the required battery size minimizes the unit system cost, while minimizing storage/discharge rates enhances battery life. The output power is smoothed as much as possible within these competing battery cost constraints. This linear programming model is scenario based – that is, the battery characteristics and behavior are determined with respect to a dictionary of "average days". In Section 3 we focus on optimal control of the battery of a predetermined size. The (dis)charge rate of the battery is optimized in order to provide a smooth output power supply to the grid.

2 Linear Programming Model

The objective of the following Linear Programming (LP) problem is to determine the optimal (minimal) size of a battery required in order to (nearly) deliver promised power to the grid, (1), such that the net output to the grid does not fluctuate beyond levels that the grid can handle; these rates of changes are referred to as ramp rate constraints and are shown by (3) and (4). The model is a scenario based problem with the scenarios reflecting various potential energy output levels from the solar panel/wind turbine. Equation (2) represents the relationship between the storage output, the solar panel input, and the net output to the grid. Equation (5) ensures that the energy storage device's charge is always non-negative. Equation (6) ensures that the storage device's charge never exceeds its maximum. Equation (7) ensures that the net output from the storage device is zero over the cycle that is being modeled, be it a day, week, month, etc. Equations (8) through (14) determine at what times the battery unit will be used in order to smooth the power supply to the grid.

Variables:
E_{max}: Maximum size of the energy storage device
E_0: Initial Charge in the energy storage device
$P^n_{o,t}$: Output power to the grid at time t for scenario n
$P^n_{s,t}$: Output power from the storage device at time t for scenario n

Parameters:
R^*_t: Maximum ramp up/down rate allowable to the grid/battery
$P^n_{i,t}$: Input from the solar panel at time t for scenario n

$$\min E_{max} - \sum_{n,t} p^n LMP_t P^n_{o,t} + \sum_{n,t} \alpha_t p^n D^n_{o,t} \tag{1}$$

$$P^n_{s,t} - P^n_{o,t} = P^n_{i,t} \tag{2}$$

$$P^n_{o,t} - P^n_{o,t-1} \leq R^{max}_t U_{t-1} + R^{up}_t V_t \ \forall t, n \tag{3}$$

$$P^n_{o,t-1} - P^n_{o,t} \leq R^{min}_t U_t + R^{down}_t W_t \ \forall t, n \tag{4}$$

$$E_o - \sum_{k=1}^{t} P^n_{s,k} \geq 0 \ \forall n, t \tag{5}$$

$$E_o - \sum_{k=1}^{t} P^n_{s,k} - E_{max} \leq 0 \ \forall n, t \tag{6}$$

$$\sum_{k=1}^{T} P^n_{s,k} = 0 \ \forall n \tag{7}$$

$$V_t - W_t = U_t - U_{t-1} \ \forall t \tag{8}$$

$$V_t \leq U_t \ \forall t \tag{9}$$

$$V_t \leq 1 - U_{t-1} \ \forall t \tag{10}$$

$$W_t \leq 1 - U_t \ \forall t \tag{11}$$

$$W_t \leq U_{t-1} \ \forall t \tag{12}$$

$$0 \leq U_t, V_t, W_t \leq 1 \ \forall t \tag{13}$$

$$U_t \in 0, 1 \ \forall t \tag{14}$$

$$-P^{max}_{s,t} U_t \leq P^n_{o,t} \leq (P^{max}_{i,t} + P^{max}_{s,t}) U_t \ \forall n, t \tag{15}$$

$$-P^{max}_{s,t} U_t \leq \bar{P}_{o,t} \leq (P^{max}_{i,t} + P^{max}_{s,t}) U_t \ \forall n, t \tag{16}$$

$$D^n_{o,t} \geq \bar{P}_{o,t} - P^n_{o,t} \ \forall n, t \tag{17}$$

$$D^n_{o,t} \geq -\bar{P}_{o,t} + P^n_{o,t} \ \forall n, t \tag{18}$$

$$U_t = 1 \text{ when battery unit is on at time } t\text{, 0 otherwise} \tag{19}$$

$$V_t = 1 \text{ when battery unit is started at time } t\text{, 0 otherwise} \tag{20}$$

$$W_t = 1 \text{ when battery unit is shutdown at time } t\text{, 0 otherwise} \tag{21}$$

$$\bar{P}_{o,t} = \text{ promised output to the grid} \tag{22}$$

$$D^n_{o,t} = \text{ deviation of real output from promised output} \tag{23}$$

A preliminary experiment was conducted with a precursor to the LP presented above. The results are presented in Figure 3. Note that the battery size requirement is rather large. This is primarily due to the fact that this scenario was generated with the goal of smoothing power over an entire 24 hour period, which caused the system to attempt to store a good deal of energy throughout the entire day and then release it throughout the night. However, this is somewhat impractical given that power consumption rates are generally lower at night, and that other traditional power systems could be utilized to provide power during the night. In the LP model presented above, we are allowed to decide *when* we would like to smoothen the power output to the grid (i.e., during the day only) via the binary U_t, V_t, and W_t variables. This should allow the required battery size to be greatly reduced.

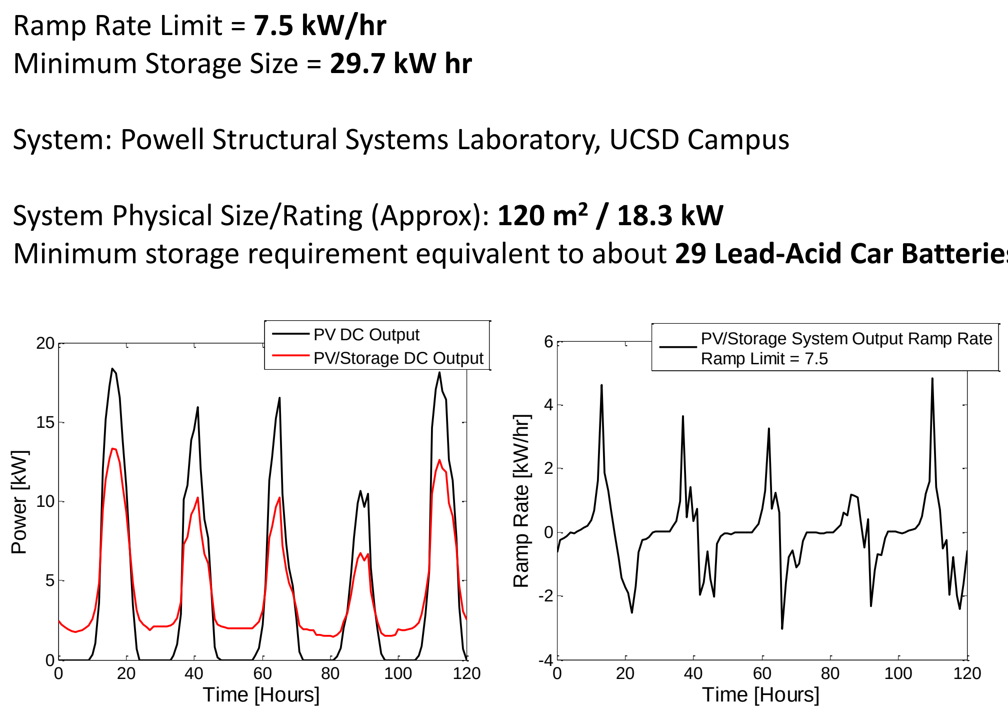

Figure 3: Battery Used to Level Power Output from Solar Panel

3 An Optimal Control Approach

Let P_I be the power output into a grid of electric power network. Due to the nature of renewable energy, fluctuation of P_I could be so significant that a storage is required as the means of control to achieve steady power flow. Let P_S be the power flow from the storage, the resulting power output to the network is denoted by P_O. The problem is to find a feedback of controlling P_S or $\dot{P}_S$ so that P_O is as steady as possible, provided that the total energy, E_S, in the storage is within its capacity. For the reason of continuous operation, we also require that the final value of E_S equals a half of the maximum storage capacity, or any other value that is appropriate.

A preliminary formulation of the problem has the following form

$$\min_{\dot{P}_S} \int_{t_0}^{t_0+T} (\lambda f(\dot{P}_O) + (1-\lambda)\dot{P}_S^2)dt$$

subject to

$$\begin{aligned}
&P_O = P_I + P_S \\
&0 \leq E_S(t) = E_S(0) - \int_{t_0}^{t} P_S(t)dt \leq E_S^M \\
&E_S(t_0) = E_{S0} \\
&E_S(t_0+T) = E_{S1}
\end{aligned}$$

In this formulation, P_I can be a known function of t, or it is a random process. In the cost function, $f(\dot{P}_O) \geq 0$ has a minimum value at $\dot{P}_O = 0$. This is to ensure that $\dot{P}_O$ is close to zero. By including $\dot{P}_S^2$ in the cost function, the speed of charging the storage is limited for the reason of battery lifespan.

3.1 Moving Horizon Optimal Control

In moving horizon optimal control, an open-loop optimal control $\dot{P}_S(t)$ is computed for a given time interval. Then this control input is updated real-time. The advantage of this approach is its capability of finding controllers with constraints. However, it requires real-time numerical solution of optimization.

For this purpose, the stabilization of P_O is formulated as a problem of optimal control. Denote $x_1 = E_S$, $x_2 = -P_S$, and the control input is

$u = -\dot{P}_S$, the velocity the battery is charged or discharged. Then the problem of optimal control is formulated as follows

$$\Phi = \min_u \int_{t_0}^{t_0+T} (\lambda f(\dot{P}_O) + (1-\lambda)u^2) dt$$

subject to

$$\begin{aligned}
&\dot{x}_1 = x_2 \\
&\dot{x}_2 = u \\
&0 \le x_1 \le E_S^M \\
&x_1(t_0) = E_{S0} \\
&x_1(t_0 + T) = E_{S1} \\
&\dot{P}_O = \dot{P}_I - u
\end{aligned}$$

The method of pseudospectral optimal control is applied to numerically solve the optimal control problem. For testing purposes, let $\lambda = 1$ and we assume a predictable variation of P_I in a five hour time interval

$$P_I = 70 \sin(2\pi t/tf), \quad tf = 5$$

To minimize the variation, we take a quadratic function

$$f(\dot{P}_O) = \dot{P}_O^2$$

If there is enough storage, then the control is able to completely stabilize P_O so that it has zero variation. However, the storage capacity may not be adequate. Figure 4 is a numerical result with battery storage capacity about 25% short of the amount required to fully stabilize the power output. In this case, the minimum cost is $\Phi = 1415$. In this computation, we allow the battery to jump start. If the initial P_S is zero, then the optimal control is shown in Figure 5. The zero initial P_I is quite restrictive. In fact, the cost, $\Phi = 5718$, is four times that of using jump start.

In the figures, it may seem like a saturation of E_s in an interval around $t = 2.5$. In fact, it is due to the inaccuracy of the plot. In a computation with enough number of nodes, for this case $N = 61$, E_s peaks at $t = 2.5$, but do not saturate in an interval around this point. By peaking at $t = 2.5$, this controller works aggressively to stabilize P_O as much as it can achieve. A more conservative controller can be computed by weighting on E_s, which is shown in the next section.

In some applications, a quadratic cost function may not serve the purpose. For example, it is important to keep $\dot{P}_O$ away from a bound. In this case, we apply a U shaped cost function $f(\dot{P}_O)$ (Figure 6). Then the control policy is much closer to piecewise linear. For instance, assuming 25% short of storage, with jump start, we have the following performance (Figure 7). In the case of continuous start, the result is shown in Figure 8.

3.2 State Feedback Control

If the fluctuation of the input power has significant random variation, a moving horizon controller may not be able to react fast enough to the random change. For this purpose, a feedback control law is desirable. Suppose

$$P_O = P_I + w_t + u$$

where w_t is a Brownian motion that represents the random part of the input power variation. Denote $x_3 = P_O$, then the problem can be formulated as follows

$$\Phi = \min_u E\left(\int_{t_0}^{t_0+T} (\lambda f(\dot{P}_O) + (1-\lambda)(x_1 - E_S^M/2)^2)dt\right)$$

subject to

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= u \\ dx_3 &= (\dot{P}_I - u)dt + \sigma dw_t \end{aligned}$$

In this formulation, the term in $(x_1 - E_S^M/2)^2$ is used to limit the magnitude of variation in the storage. By increasing the value of λ, the controller is less aggressive and E_s tends to stay away from its capacity limit. For instance, if $\lambda = 1/3$ and without random variation, Figure 9 shows the control performance

If

$$f(\dot{P}_O) = \dot{P}_O^2$$

then

$$
\begin{aligned}
& E\left(\int_{t_0}^{t_0+T}(\lambda f(\dot{P}_O)+(1-\lambda)(x_1-E_S^M/2)^2)dt\right) \\
& = E\left(\int_{t_0}^{t_0+T}(\lambda((\dot{P}_I-u)^2+2\sigma(\dot{P}_I-u)\dot{w}_t+(\sigma\dot{w}_t)^2)+(1-\lambda)(x_1-E_S^M/2)^2)dt\right) \\
& = \int_{t_0}^{t_0+T}(\lambda((\dot{P}_I-u)^2+\sigma^2)+(1-\lambda)(x_1-E_S^M/2)^2)dt
\end{aligned}
$$

We can remove the constant term σ^2 from the cost function

$$
\Phi = \min_u \int_{t_0}^{t_0+T}(\lambda(\dot{P}_I-u)^2+(1-\lambda)(x_1-E_S^M/2)^2)dt
$$

The optimal cost is a functional $\Phi(t, x_1, x_2, \dot{P}_I)$ and the optimal control law is also a functional $u(t, x_1, x_2, \dot{P}_I)$. They satisfy the following Hamilton-Jacobi-Bellman (HJB) equation

$$
\begin{aligned}
& \frac{\partial\Phi}{\partial t}+\min_u\left(\frac{\partial\Phi}{\partial x_1}x_2+\frac{\partial\Phi}{\partial x_2}u+\frac{\partial\Phi}{\partial x_3}(\dot{P}_I+u)+\frac{\sigma^2}{2}\frac{\partial^2\Phi}{\partial x_3^2}+\lambda(\dot{P}_I-u)^2+(1-\lambda)(x_1-E_S^M/2)^2\right) \\
& = 0 \\
& \Phi(t_0+T, x_1, x_2, x_3, \dot{P}_I) = 0
\end{aligned}
$$

The optimal control has the form

$$
u^* = -\frac{1}{2}\left(\frac{\partial\Phi}{\partial x_2}+\frac{\partial\Phi}{\partial x_3}+2\lambda\dot{P}_I\right)
$$

Ideally, we would like to analytically solve the HJB equation so that the feedback controller is derived explicitly. Such a controller avoids the online numerical optimization, which significantly reduces the computational load for real-time applications.

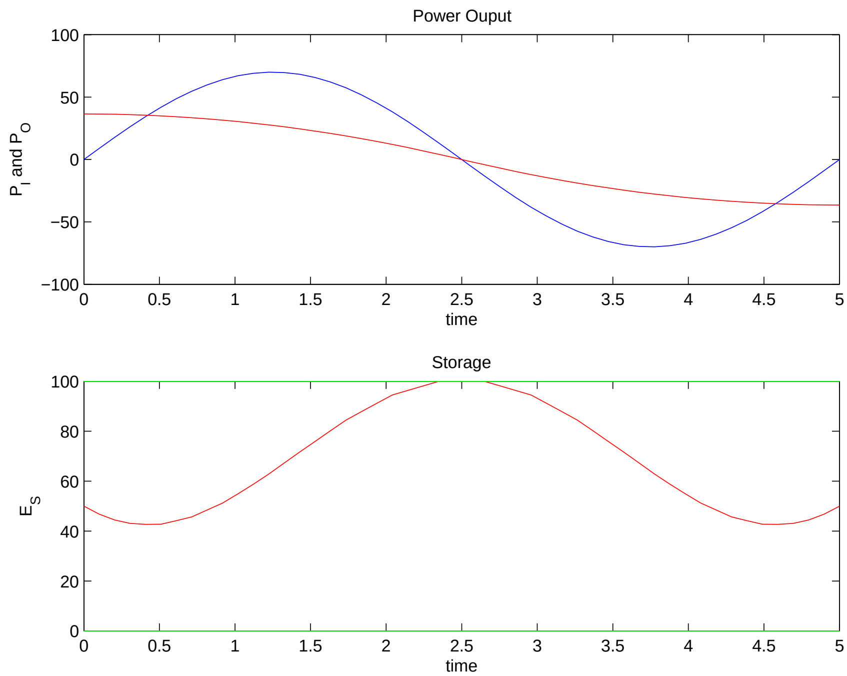

Figure 4: P_I (blue) and P_O (red) vs time; Total storage vs time

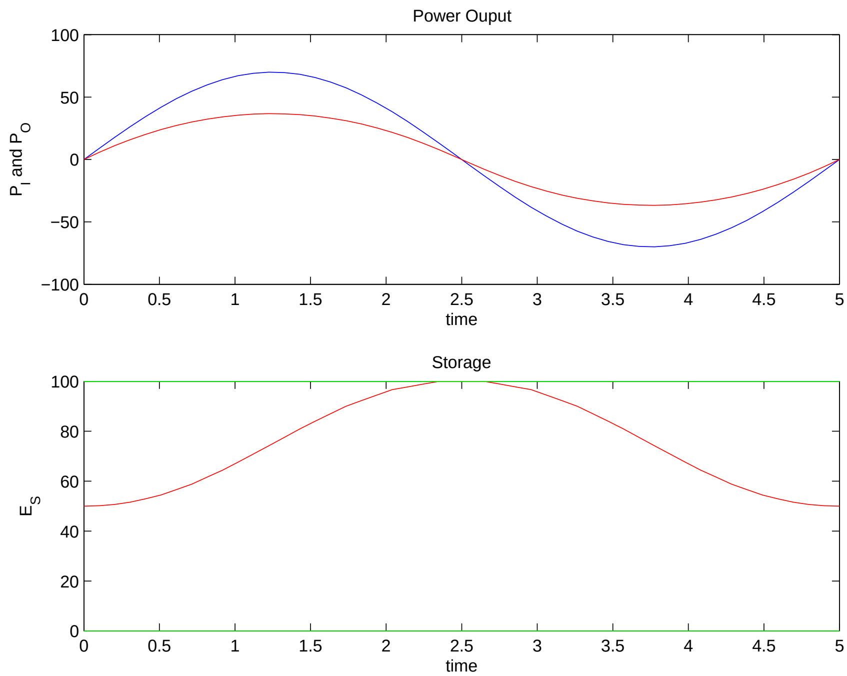

Figure 5: P_I(blue) and P_O(red) vs time; Total storage vs time

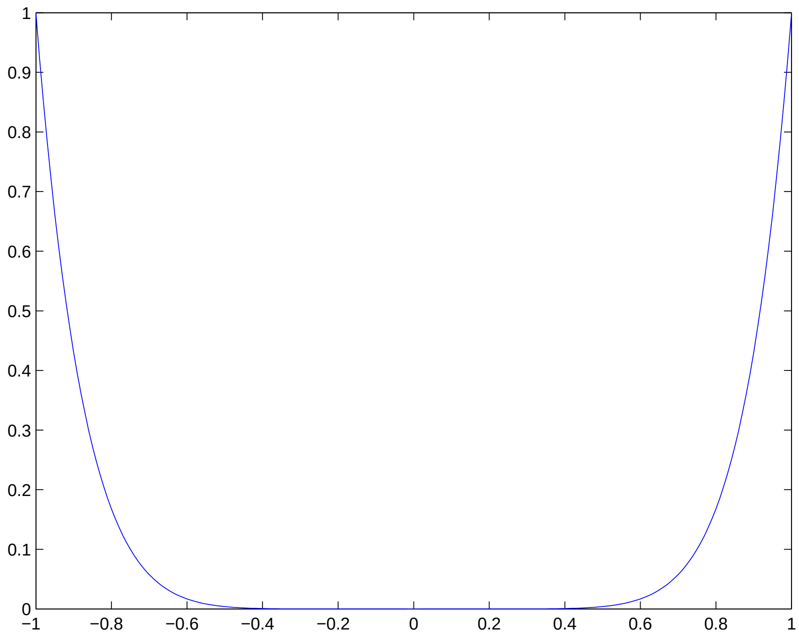

Figure 6: $f(\dot{P}_O)$

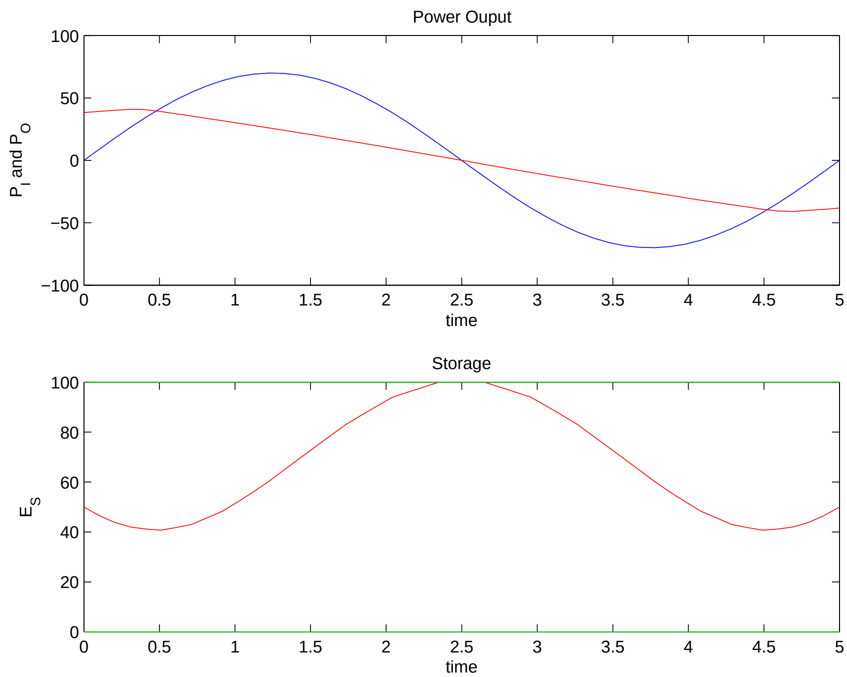

Figure 7: P_I and P_O vs time; Total storage vs time

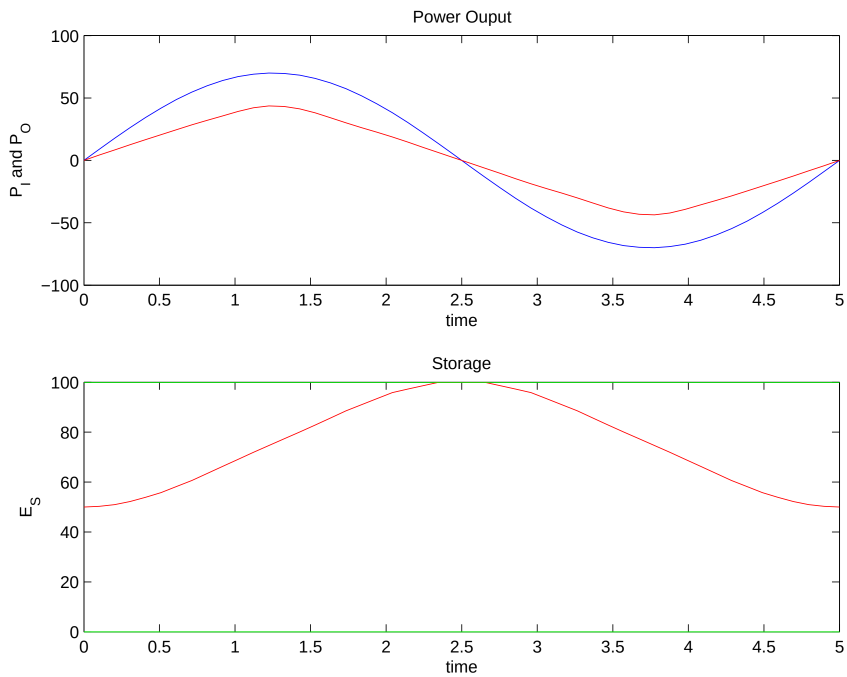

Figure 8: P_I and P_O vs time; Total storage vs time

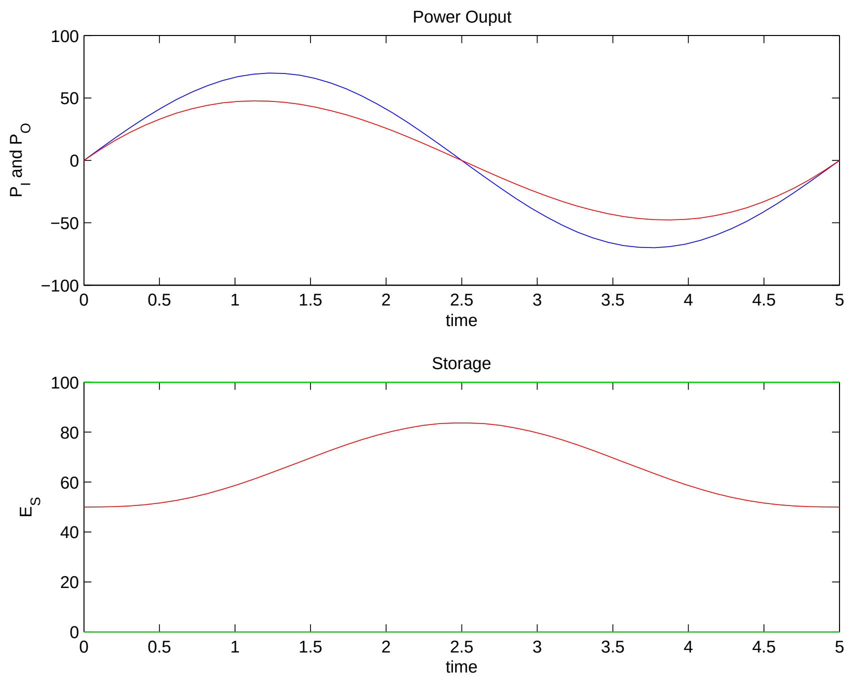

Figure 9: P_I and P_O vs time; Total storage vs time