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Title:

Model Predictive Optimization Based Energy Storage System in Distributed System

Presented By:

- **ABOUBAKER RICHE**

Supervisor:

Dr.Boutora Saliha

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Acknowledgment

In the name of Allah, the Most Merciful and the Most Gracious,

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Abstract:

Model Predictive Control (MPC) has shown great success in various industrial applications, where they to have constraints on both , state and inputs. This ensures that processes will be run within tight performance specifications.

The main goal of this project is to develop an MPC controller they will improve the performance of the storage system , by controlling the power flow between the battery energy storage system (BESS) and the supercapacitor (SC).

To accomplish task stressing grid-forming hybrid energy storage systems and the supercapacitor's state of charge (SoC) by simulate rapid load variations and fast photovoltaic (PV) power fluctuations , also developing an MPC controller is depends to efficient controlling power flow , restore to the SoC of SC after sudden load changes and limits its SoC variation in a predefined range, to ensure the continuous operation of SC.

The performance of the proposed approach is then simulated using MATLAB/Simulink.

Nomenclature

MPC - Model Predictive Control

PV - Photovoltaic

RES - Renewable Energy Sources

I=current (A)

V=Voltage (V)

DER=distributed energy resources

PHEV=plug-in hybrid Electrical Vehicle (PHEV)

ESS = Energy Storage System

BESSs=battery storage systems

FITs = feed-in tariffs

PID= Proportional-Integral-Derivative

OPC= Optimization and Prediction Control

SoC=State of Charge

SoH=State of Health

DoD = Depth of Discharge

ESR = equivalent series resistance

PI = Proportional-Integral

CPS =Constant Power Source

CPL = Constant Power Load

HESS= Hybrid Energy storage system

SC= Super-Capacitor

MGs=Microgrids

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1.1 Introduction:

To meet the global greenhouse emission reduction targets outlined in the Paris Agreement and ensure that the global average temperature rise remains well below 2°C compared to pre-industrial levels, future power energy systems will heavily rely on renewable energy sources like wind and solar. However, due to the inherent unpredictability and intermittency of renewable sources, it's essential to devise a balancing mechanism that can align electricity supply with demand consistently.

The most promising solution for balancing renewable energy sources with consumer demand involves the deployment of electric batteries [1; 2]. These batteries are charged during periods of excess or low-cost electricity (typically when demand is low) and discharged when energy becomes scarce or expensive (typically during high-demand periods). Since batteries have limitations in terms of maximum capacity and discharge rate, a controller is needed to determine the optimal times for charging and discharging. Moreover, the battery's expected lifespan depends on its operational conditions, including the charging strategy [3], so the controller must aim to extend rather than expedite the battery's life.

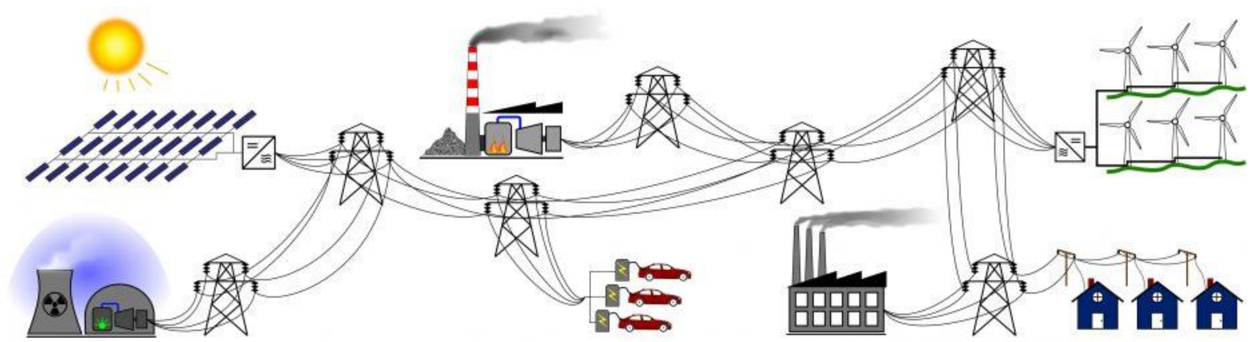


Figure 1.1 Grid Integration of Renewable Energy Sources

Model Predictive Control (MPC) has demonstrated significant success in various industrial applications [4] and has even been applied to smooth the power output of wind generators [1]. MPC controllers offer the advantages of both feedback and non-feedback control systems, allowing them to predict system disturbances and respond to them if they occur unexpectedly. Furthermore, constraints can be easily incorporated, ensuring that the controller avoids actions that could violate these constraints, which is crucial in many scenarios. Therefore, MPC has been selected for addressing the two control challenges discussed in this project. As MPC controllers require a predictive model for effective control, this work also involves the development and validation of a model for a typical Li-ion battery.

1.2 Energy Storage in PV System:

1. 2.1 Introduction :

Energy storage plays a pivotal role in the integration and optimization of photovoltaic (PV) systems within the energy landscape. With the increasing adoption of renewable energy sources, such as solar power, there is a growing need to efficiently capture, store, and utilize the energy generated by PV systems. This work explores the significance, challenges, and strategies associated with energy storage in PV systems. [5]

1. 2.2 How PV Systems with Storage work

In a PV system with storage, the solar panels generate electricity during the day, fulfilling the energy needs of homes while potentially producing surplus power. In a conventional setup, any excess electricity is sent back to the grid, often resulting in credits on users electricity bill.

However, when a PV system is equipped with energy storage, this surplus electricity is intelligently stored in batteries or accumulators. These energy storage units play a crucial role in harnessing the excess energy produced during daylight hours for use when the PV system is unable to generate electricity, such as at night or on cloudy days.

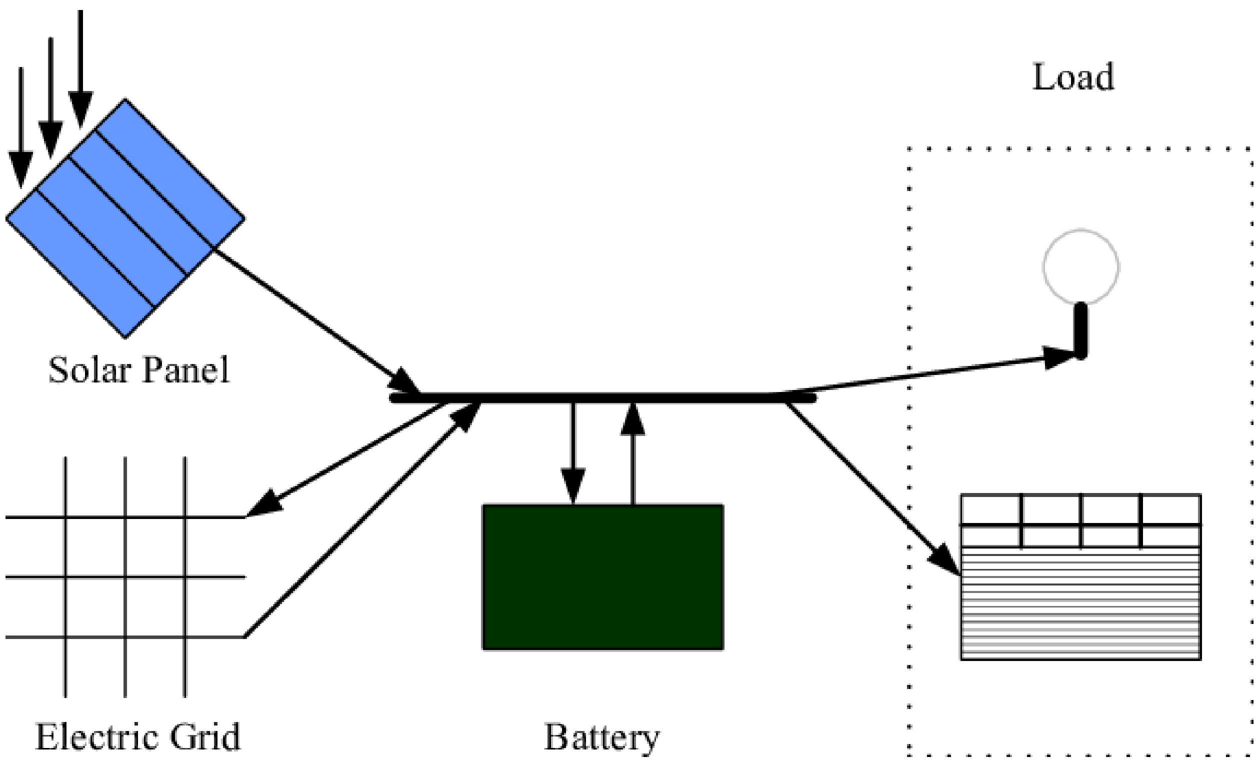


Figure 1.2 Grid-connected PV system with battery storage and loads.

By adopting this approach, the reliance on the grid can significantly be reduced, potentially cutting electricity expenses by up to 50%, depending on the capacity of the energy storage system. [6]

Energy storage systems are particularly valuable for homes that operate off-grid, where there is no connection to the electrical grid. This scenario often applies to remote locations like mountain lodges or properties intentionally powered entirely by renewable energy sources.

Moreover, storage systems are beneficial for households that consume more energy during the evening and night, even if they generate ample solar energy during the day. They act as a buffer, ensuring that surplus daytime energy is available when needed most.

To determine if energy storage makes financial sense, a simple meter reading can provide insights: If the energy exported to the grid equals or exceeds the consumed energy, then investing in storage to use that surplus energy later is indeed a cost-effective choice. [7]

1.3 The history of Model Predictive Control:

(MPC) traces its roots to the mid-20th century. In the 1950s and 1960s, MPC began as a concept in the field of process control and was primarily used in industrial applications to optimize the control of complex systems.

In the 1970s, MPC gained traction in the field of economics and was employed in economic models and financial systems. Its ability to handle predictive control problems with constraints made it an appealing choice for various applications.

By the 1980s, MPC had evolved significantly, and researchers started exploring its applications in fields such as robotics, aerospace, and automotive industries. It was recognized for its effectiveness in controlling dynamic systems while considering predictive information.

In the 1990s, advancements in computer technology and control algorithms propelled MPC into more diverse fields, including energy management and environmental control systems. It became a valuable tool for optimizing energy consumption and minimizing environmental impact.

In the 21st century, MPC continued to expand its reach, finding applications in fields like autonomous vehicles, renewable energy systems, and smart grids. Its adaptability and ability to handle complex, dynamic processes made it a critical component of modern control systems.

Today, MPC plays a crucial role in various industries, offering solutions for optimizing processes, improving efficiency, and addressing complex control challenges. Its history reflects its evolution from an industrial control concept to a versatile and essential tool across multiple domains. [8]

1.4 Model Predictive Control

Model Predictive Control (MPC) is a sophisticated control strategy used in various domains, offering flexibility and optimization in complex systems. In the realm of control systems, MPC is akin to a hybrid vehicle, combining different components to achieve specific objectives.

Much like a hybrid vehicle blends an internal combustion engine (ICE) with an electric propulsion system, MPC blends predictive control with optimization techniques. This combination can be tailored to diverse applications and goals, whether it's achieving superior system performance or optimizing resource utilization.

Just as hybrid vehicles use different energy sources, MPC can be configured with various control objectives, allowing it to adapt to changing requirements and constraints. This flexibility empowers MPC to select the most suitable control strategies for different scenarios, much like how hybrid vehicles can switch between power flow paths to meet specific needs. [9]

In the context of energy storage, MPC can be likened to the choice of energy storage device in a hybrid vehicle, such as electrochemical batteries or super-capacitors. These choices depend on specific requirements and desired outcomes.

Overall, much like hybrid vehicles offer multiple configurations to meet various needs, MPC provides a versatile control strategy that can be tailored to different applications, delivering optimal results based on specific objectives and constraints. [10]

1.5 Key Components and Characteristics of MPC:

Model Predictive Control (MPC) is a highly effective control strategy employed across diverse domains, particularly in complex systems like energy management. At its core, MPC relies on several fundamental components and exhibits key characteristics that underpin its success. A critical aspect is the incorporation of a prediction horizon, enabling MPC to anticipate future system behavior accurately. Within this predictive framework, a control horizon defines shorter intervals for determining optimal control actions, ensuring adaptability to evolving conditions. Dynamic models, accounting for time-dependent variables, form the foundation of MPC, enabling it to make informed decisions based on system dynamics.

Another pivotal aspect is the formulation of a cost function that quantifies specific objectives, such as minimizing energy consumption or optimizing system performance. MPC also embraces constraints to maintain system stability and safety, preventing operations from exceeding predefined limits. Furthermore, it operates within a feedback loop, constantly updating predictions and control actions based on real-time measurements, offering dynamic responsiveness.

Notably, MPC excels in multi-variable control scenarios, efficiently managing interconnected components within intricate systems. Its robustness against disturbances and uncertainties enhances its reliability in real-world applications. MPC's iterative optimization approach allows it to identify optimal control actions, contributing to enhanced system efficiency. Its adaptability and versatility make it suitable for a wide array of applications, ranging from renewable energy resource management to industrial process control. Enabled by advancements in computational power, MPC has found practical real-time implementations, empowering its adoption in diverse fields. Additionally, it offers transparency in decision-making, aiding in understanding and optimizing system behavior. Collectively, these components and characteristics underscore MPC's status as a potent and flexible tool for optimizing complex systems and improving their overall performance. [11]

1.6 Model Predictive Control in Energy Distribution Systems:

Model Predictive Control (MPC) technologies encompass various control strategies applied in energy distribution systems across diverse industries. MPC combines multiple components to enhance the overall performance and efficiency of distribution networks. The versatility of MPC lies in its ability to optimize energy distribution, reduce resource wastage, and provide superior control, making it increasingly popular across different distribution contexts. This adaptability allows MPC to significantly impact efficiency and operational outcomes while enhancing the overall management of distribution systems. [12]

1. 6.1 MPC for Energy Optimization

MPC strategies in energy systems aim to maximize efficiency and effectiveness in resource allocation. MPC optimizes power generation and distribution by considering predictive models and real-time data. This approach allows MPC to operate efficiently and adapt to changing energy demands while minimizing waste.

1. 6.2. MPC Technologies in Energy Distribution Systems

The application of Model Predictive Control (MPC) technologies is explored within energy distribution systems, delving into their significant impact and versatility in the management and optimization of energy networks. This overview serves as the groundwork for a comprehensive examination of MPC's role in addressing critical challenges and improving the efficiency, reliability, and sustainability of distribution systems.

1.7 Integration of Renewable Energy Sources:

MPC technologies play a pivotal role in addressing the integration challenges associated with renewable energy sources (RES). By harnessing predictive models and control strategies, MPC aids in seamlessly incorporating intermittent RES like solar and wind into the grid. This integration is essential for reducing reliance on fossil fuels, mitigating environmental impacts, and meeting sustainability goals. [13]

1.7.1 Demand Response and Load Management

Efficient demand response and load management are imperative for grid stability and cost optimization. MPC excels in this regard by providing real-time insights into energy consumption patterns, enabling utilities to implement demand-side management strategies effectively. It facilitates peak shaving, load shifting, and dynamic pricing, ultimately enhancing grid reliability and reducing operational costs. [14]

1.7.2 Grid Optimization and Control

The intricacies of energy distribution grids demand sophisticated control mechanisms. MPC technologies offer a robust solution by optimizing grid operations in real time. They ensure that electricity generation, transmission, and distribution are coordinated efficiently, minimizing losses and improving overall system reliability. [15]

1.7.3 Asset Management and Maintenance

Asset management and maintenance are crucial for prolonging the lifespan of grid components and reducing downtime. MPC aids in predictive maintenance by continuously monitoring the condition of critical assets. This proactive approach minimizes disruptions, lowers repair costs, and enhances the longevity of grid infrastructure. [16]

1.7.4 Microgrid and Decentralized Energy Systems

The rise of microgrids and decentralized energy systems necessitates advanced control strategies. MPC is instrumental in managing the dynamic interactions between distributed energy resources (DERs), energy storage, and local demand. It ensures seamless grid islanding, energy sharing, and optimal utilization of resources within microgrid ecosystems. [17]

1.7.5 Resilience and Grid Security

Grid resilience and security are paramount concerns in the face of natural disasters and cyber threats. MPC technologies bolster grid resilience by enabling rapid response to contingencies and optimizing energy flow rerouting. They enhance grid security through anomaly detection and threat mitigation. [18]

1.7.6 Environmental Sustainability:

Environmental sustainability is at the forefront of energy distribution systems. MPC aids in reducing carbon emissions by optimizing the use of renewable energy sources and minimizing the reliance on fossil fuels. It supports the transition towards cleaner, more sustainable energy networks.

In the subsequent sections, we delve deeper into each of these MPC applications, showcasing their real-world implementations, benefits, and emerging trends in energy distribution systems.

1.8 MPC for Resource Management:

MPC strategies in energy systems provide assistance in managing energy resources, optimizing functions such as start-stop operations, torque enhancement, and regenerative braking. Similar to the objectives of mild hybrids, MPC operates with the goal of improving resource efficiency while reducing emissions and waste. [19]

1.9 MPC with External Charging:

MPC can incorporate external charging capabilities, allowing it to store and manage energy from external sources efficiently. This feature enhances system performance and reduces reliance on fossil fuels, similar to the advantages of plug-in hybrid (PHEV) vehicles. [20]

Benefits and Considerations of MPC While MPC offers numerous benefits in optimizing energy systems, it also presents certain challenges and considerations. These include the cost, volume, and lifespan of energy storage systems (ESS). Careful evaluation of these factors is essential to harness the full potential of MPC in energy management.

MPC technologies offer versatile solutions for optimizing energy resource utilization, improving efficiency, and adapting to changing energy demands across diverse energy systems and applications.

1.10 Conclusion:

In conclusion, we provided a comprehensive overview of various aspects related to distribution systems and Model Predictive Control (MPC). The last decade has witnessed an exponential growth in global electricity production from photovoltaic (PV) plants, driven by a significant reduction in PV module costs. This surge in PV adoption has highlighted the challenges faced by grid operators in managing power from intermittent sources. The integration of battery storage systems (BSSs) has emerged as a solution, especially with declining prices.

emphasizing the importance of prioritizing self-consumption of PV-generated power, particularly in regions where feed-in tariffs (FITs) for residential solar energy have diminished. Research efforts have explored different methods to maximize energy self-sufficiency, but certain critical aspects of BSSs, such as battery charging profiles and health degradation, have received less attention.

Furthermore, we introduced the concept of a capacity model predictive optimization based energy storage system in PV systems. Such systems play a crucial role in harnessing surplus daytime energy for nighttime and cloudy day use, potentially reducing grid dependence by up to 50%.

The historical evolution of Model Predictive Control (MPC) was also presented, tracing its roots from process control to economics, robotics, and various other domains. MPC's adaptability and effectiveness in controlling dynamic systems were highlighted, leading to its widespread adoption in modern control systems.

The key components and characteristics of MPC were discussed, emphasizing its predictive framework, cost functions, constraints, feedback loop, and multi-variable control capabilities. MPC's adaptability, real-time responsiveness, robustness, and suitability for diverse applications were highlighted.

Finally, the chapter explored the diverse applications of MPC in energy distribution systems, including renewable energy integration, demand response, grid optimization, asset management, microgrids, grid security, and environmental sustainability.

It provides valuable insights into the role of MPC in addressing the complex challenges of modern energy distribution systems and highlights its potential to enhance efficiency, reliability, and sustainability across various domains.

Chapter 02: Foundations and Models for Advanced Control in Energy Storage Systems

2-1. Theoretical Foundation of MPC

Model Predictive Control (MPC) operates through an iterative, finite-horizon optimization process applied to a plant model. At each time instant "t," the current state of the plant is sampled, and a control strategy that minimizes costs is computed for a short future time interval $[\mathrm{t}, \mathrm{t}+\mathrm{T}]$. This calculation involves the use of numerical minimization algorithms. Specifically, an online, on-the-fly calculation explores possible state trajectories originating from the current state. These trajectories are determined by solving Euler–Lagrange equations to identify the control strategy that minimizes costs until time $t+T$.

However, only the initial step of this calculated control strategy is executed. Following this execution, the plant state is once again sampled, and the entire process is repeated, beginning with the updated current state. This iterative approach results in a continuous shift of the prediction horizon forward in time. Consequently, MPC is often referred to as receding horizon control.

Although this method may not achieve optimality, it has proven to yield highly effective results in practice. Significant academic research has focused on developing rapid solutions for Euler–Lagrange equations, understanding the global stability characteristics of the local optimization within MPC, and, in general, enhancing the effectiveness of the MPC technique. [43, 44]

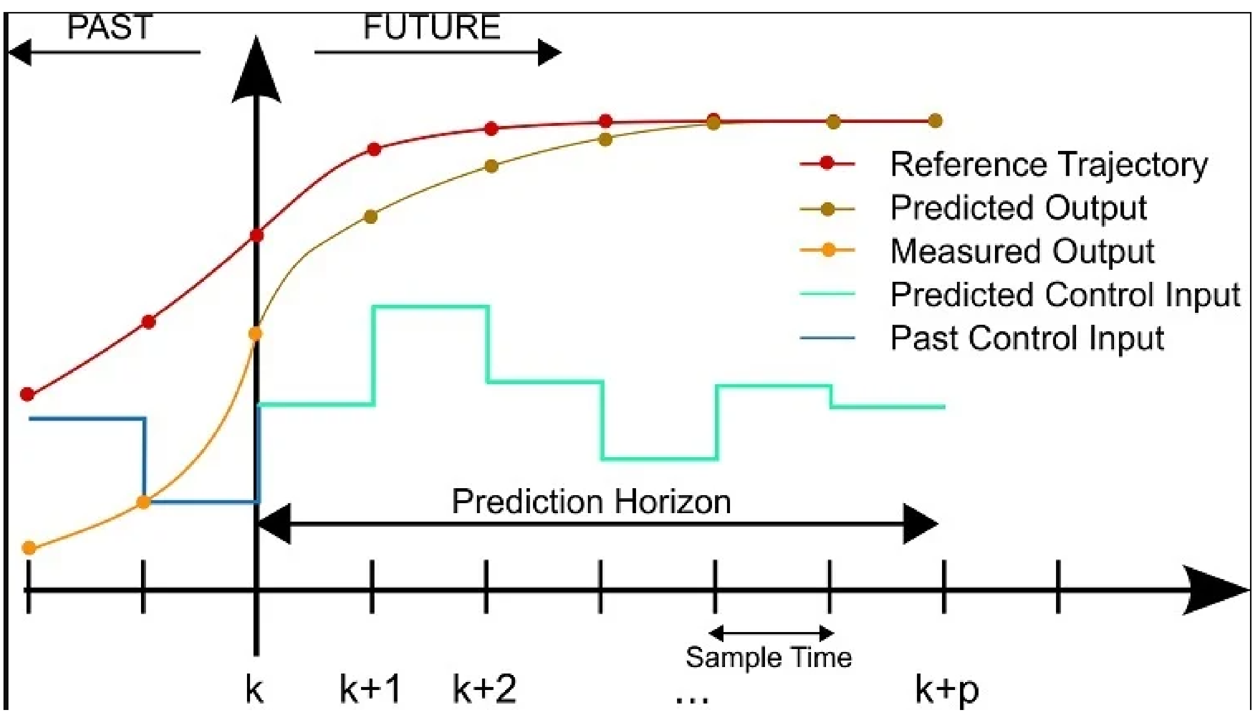


Figure 2.1 A discrete MPC scheme.

2.2 PID or MPC:

Traditional control methods, exemplified by PID (Proportional-Integral-Derivative) control, primarily harness present and past measurements for system regulation. PID, while highly effective, doesn't explicitly leverage the system's dynamic properties when issuing commands to the manipulated variables. Instead, the optimization of the closed-loop system's performance is achieved by tuning the proportional, integral, and derivative terms. Based on engineers community of industrial, PID is still the first choice for industrial feedback control mainly due to the ease of understanding its operation, ease of tuning and its widespread use in the industry. Control engineers are using creative techniques to handle the limitations of PID. [22]

The question now is when should engineers go for MPC (Model Predictive Control) instead of PID (Proportional-Integral-Derivative) control?

The flow chart below as a guideline, helps the engineer decide when is the usage of MPC Supported in the design.

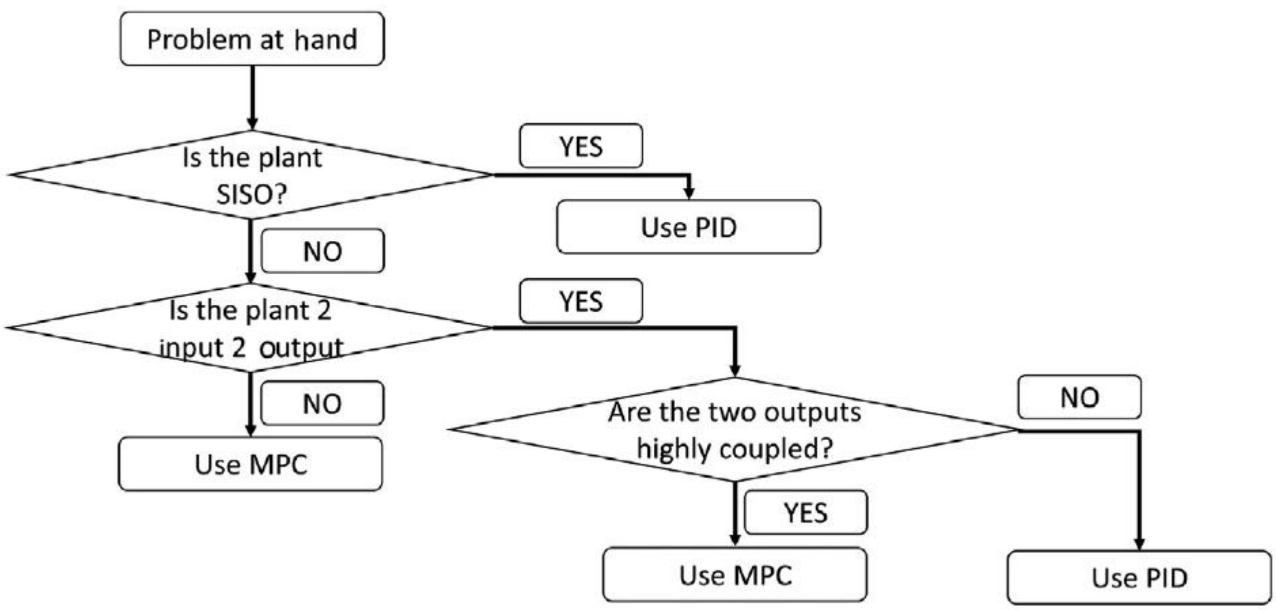
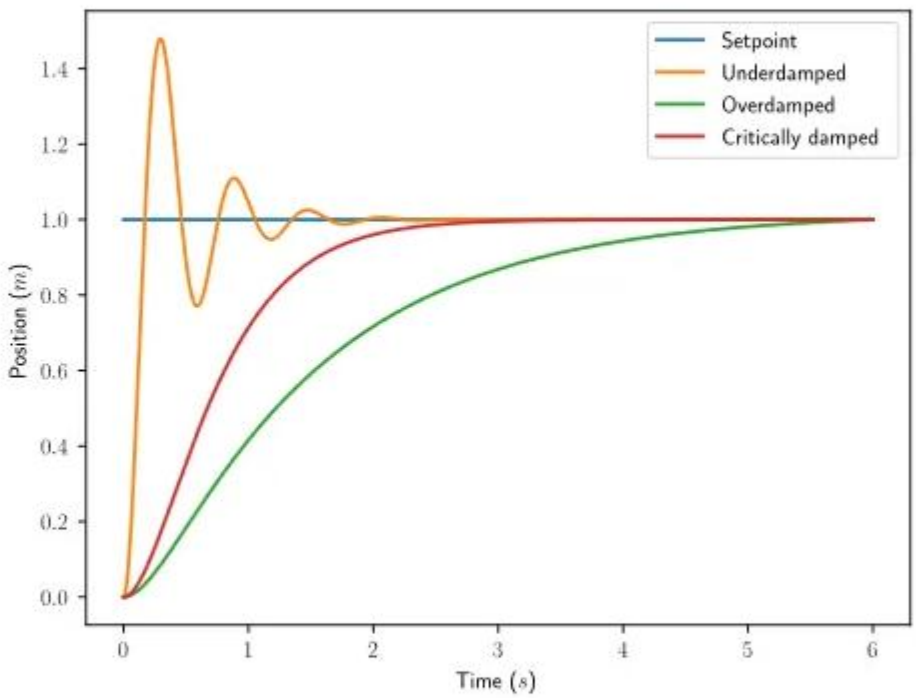


Figure 2.2 Flow chart PID or MPC

2-3 Understating MPC through PID basics:

MPC controller depends on a mathematical model that represents the behavior of the real-world physical system that it is controlling the best (optimal) path.

The controller has common elements with MPC. It would serve as a stepping stone to understanding the fundamentals of MPC. [22]



2.3 PID BASICS

Tuning Red seems to yield the best tracking. Tuning Black has overshoot which is highly undesirable for speed control.

The hypothetical controller simulates PID tunings internally, computes tracking errors, and autonomously selects the best tuning within a prediction horizon, laying the groundwork for MPC's predictive capabilities.

MPC optimizers typically go through more than PID iterations to find the optimal control solution. Moreover, the optimization process is repeated at each time step, allowing for adaptive control. This ability to iterate and optimize at every step is a fundamental aspect of MPC, enabling it to adapt to changing conditions and provide improved results. [23]

Overall, this section demonstrates how the control horizons in MPC play a crucial role in balancing computational demands with control performance, emphasizing the flexibility and adaptability of MPC compared to traditional PID control.

2-4 Introduction to MPC:

Model Predictive Control, as implied by its name, is a control methodology rooted in feedback systems, prominently relying on a mathematical model. It equally depends on a dynamic optimization solver functioning in real-time. MPC is alternatively referred to as "receding horizon control" and "quadratic programming control." A novel terminology for MPC is "Optimization and Prediction Control (OPC)," a nomenclature devised by its creators to emphasize the integral optimization aspect of MPC. [22]

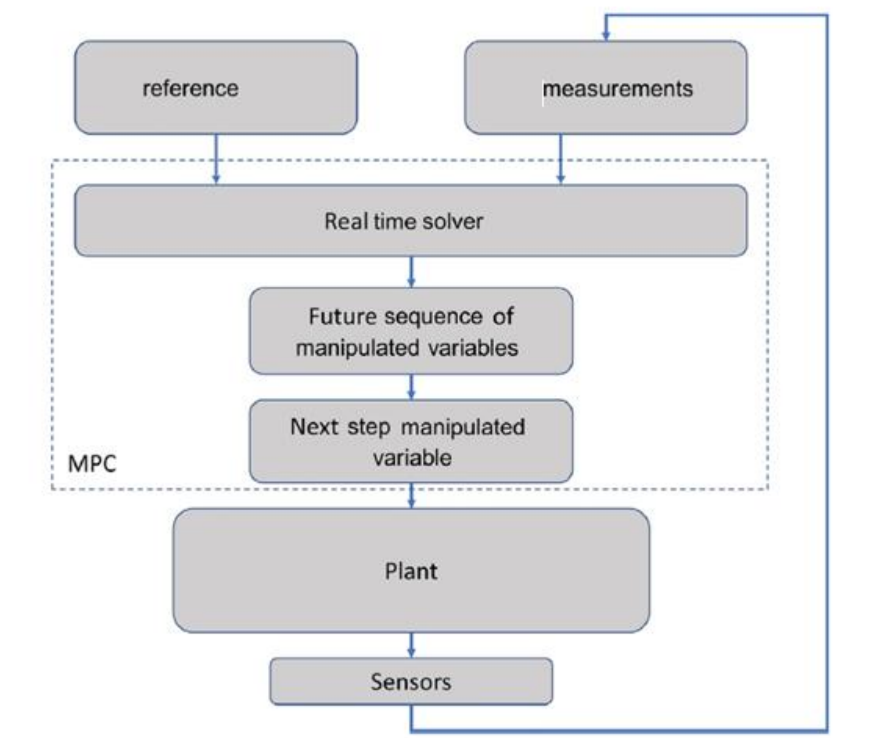


Figure 2.4 Simplified Block diagram of MPC.

In Figure 2.4 The tracking error is one part of the cost function [20]. The cost function of MPC is made of four elements:

$$J(z_k) = J_y(z_k) + J_u(z_k) + J_{\Delta u}(z_k) + J_\varepsilon(z_k) \quad [20]$$

z_k is the sequence of manipulated variables from sample k to k1p_1.

J_y is the cost function for output reference tracking (or tracking error)

J_u is the cost function for manipulated variable tracking (or deviation from nominal manipulated variable)

$J_{\Delta u}$ is the cost function for change in manipulated variables

J_ε is the cost function for constraint violations [24] .

Figure 2.5 shows a detailed block diagram of MPC as implemented in MPC Toolbox documentation.

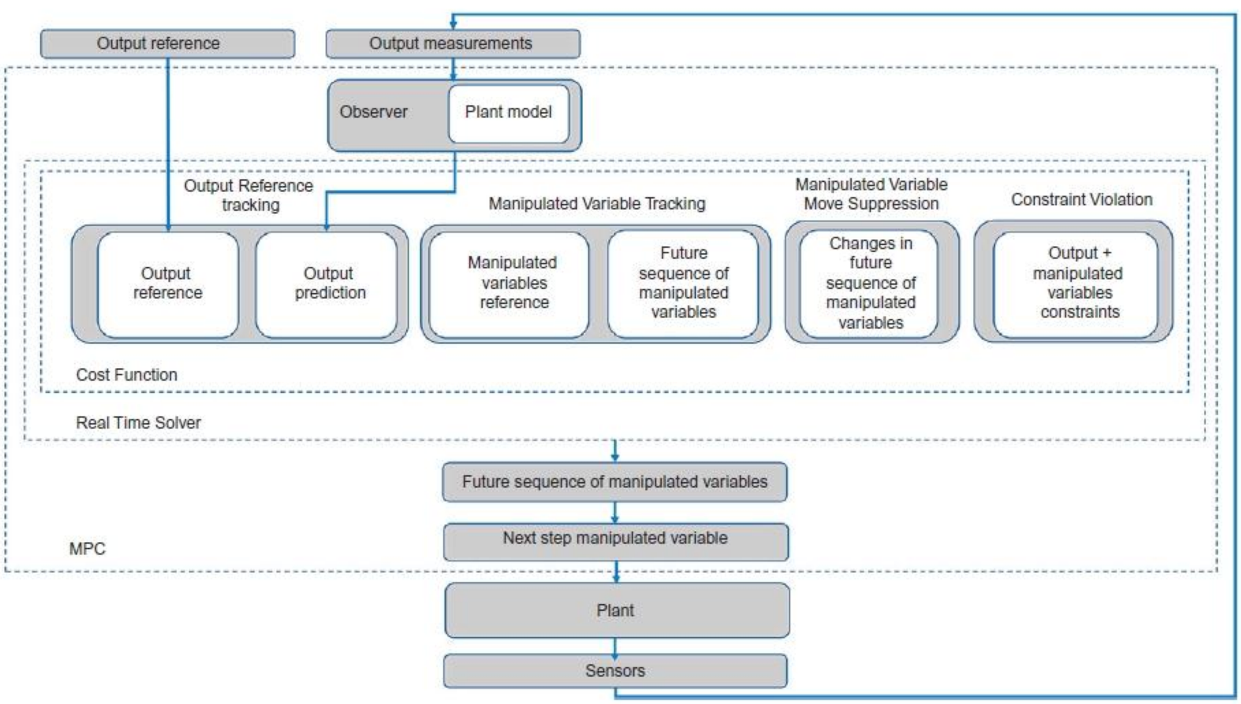


Figure 2.5 Detailed Block diagram of MPC.

The dashed-line block Cost Function shows the four elements of cost function equation .
In MPC, we rely on output measurements to continually adjust our system observer. This observer helps us forecast how the plant will behave in the upcoming prediction horizon. A crucial aspect of MPC operation is that the real-time solver calculates a sequence of future control actions over the entire control horizon, but it only sends one of those commands to the actuators for the next time step. At each subsequent time step, we use sensory data to correct and update the observer values, considering the actions taken, and then we repeat the optimization process to determine the best sequence of control actions for the entire prediction horizon. [24]

2.5 Battery modeling

As digitalization continues to advance and smart homes become increasingly prevalent, the number of battery-powered devices in our households has risen significantly. Moreover, the generation of energy from renewable sources like photovoltaic and wind systems is subject to environmental fluctuations, leading to a growing reliance on battery storage to ensure a consistent energy supply [25; 26]. Additionally, batteries play a pivotal role in electric vehicles and hybrid electric vehicles [27]. While batteries operate based on a common principle, involving the movement of electrons from the anode to the cathode, their diverse materials result in varying standard potentials. The presence of an electrolyte facilitates the flow of charge-balancing ions [28]. However, the choice of electrode and electrolyte materials imparts distinct properties to batteries, making them suitable for different applications. When modeling batteries, key characteristics that warrant consideration include:

- Nominal voltage: This refers to the battery's specified output voltage. While the battery voltage typically stabilizes around the nominal voltage under a constant load, it may exhibit variations based on the battery's current state of charge.
- Nominal capacity: The nominal capacity represents the maximum energy storage capacity of the battery. Over time, batteries may experience a reduction in their capacity due to aging.
- Power density: Power density signifies the amount of energy stored in the battery per unit of weight.

- Power rating: The power rating denotes the maximum amount of energy that a battery can deliver at a single instance.

Various types of batteries employ different electrode materials such as NiCad, NiMH, and Lead-acid, but Li-ion batteries are prevalent in consumer electronics due to their high power density and lightweight properties. However, it's important to handle them with care as they can be hazardous if mishandled, potentially leading to explosions. Safety precautions include avoiding charging beyond the maximum safe voltage, discharging below the minimum, or applying excessive charging current, and such specifications are typically provided in the battery's datasheet. To mitigate these risks, protection circuits are often integrated into these batteries. [29]

While a battery is in operation, its condition undergoes changes that can be characterized by several key parameters:

- State of Charge (SoC): SoC indicates the amount of energy presently stored in the battery relative to its usable capacity.
- State of Health (SoH): SoH is an indicator that represents the condition of a battery throughout its lifespan, ranging from 0 to 1. The calculation of SoH depends on the specific application, with capacity, internal resistance, and self-discharge being the three main factors considered. In our context, capacity is the primary factor used for calculating SoH.
- Voltage: Voltage refers to the measured electrical potential across the terminals of the battery.
- C-rate: The C-rate measures the rate of charge or discharge and is expressed in C, which is the battery's Ampere-hour capacity divided by one hour.
- Depth of Discharge (DoD): DoD signifies the fraction of a battery's capacity that has been utilized during a single discharge cycle. Most manufacturers specify a maximum DoD for optimal performance; exceeding this limit can lead to a decrease in the battery's SoH.

2.6 Related works :

Within the realm of literature, numerous models have been developed to simulate the behavior of lithium-ion (Li-ion) batteries [30; 31; 32]. These models often fall into the categories of electrochemical and analytical models, which typically involve solving complex partial differential equations. This process demands a significant amount of time and mathematical expertise. Notable examples of such models include the Shepherd model and the Generic battery model [33]. One limitation of these models is their assumption that internal resistances remain constant, making them unable to accurately represent the aging effects of batteries. However, research has shown that analytical models capable of addressing lithium-ion cell aging can be devised [34]. Such models prioritize capturing the overarching system-level behavior of batteries, such as runtime and capacity, and are well-suited for modeling aging processes.

Among these models, equivalent circuit-based models are the most prevalent. They provide valuable information about current (I) and voltage (V), yielding more precise results and offering an intuitive framework for engineers. Generally, electrical models for Li-ion batteries can be broadly categorized into three groups: Thevenin-based models, impedance-based models, and runtime-based models.

2.6.1 Impedance-Based Model: The impedance-based model, as illustrated in Figure 2.1, relies on electrochemical impedance spectroscopy to create an AC-equivalent impedance (ZAC) in the frequency domain [36]. The process of fitting ZAC to impedance spectra is intricate and lacks intuitiveness. Notably, one of the primary battery characteristics is State of Charge (SoC), representing the fraction of stored energy within the battery. However, the impedance-based model is designed for a fixed SoC and temperature configuration [35]. Given our specific problem, which involves charging and discharging the battery to observe its effects on the model, this approach is not suitable.

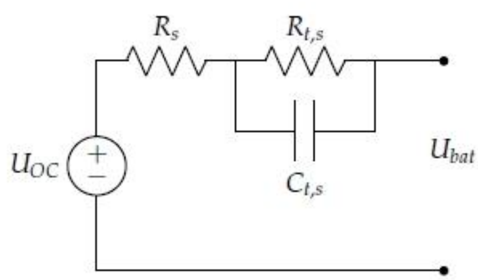
2.6.2 Thevenin-Based Model: The simplest rendition of the Thevenin-based model, depicted in Figure 2.2a, comprises a voltage source (UOC), a series resistor (Rs), and a resistor-capacitor (RC) circuit (Rt,s, Ct,s). In this model, the voltage UOC is presumed to remain constant throughout all simulations, preventing the capture of runtime information and DC response. Consequently, it cannot replicate scenarios involving battery charging or discharging. The series resistor Rs serves to depict instantaneous voltage drops, while the RC circuit is essential for modeling the transient behavior of the battery.

Therefore, the simple form of Thevenin-based model can model only short-term transient dynamics of the battery.

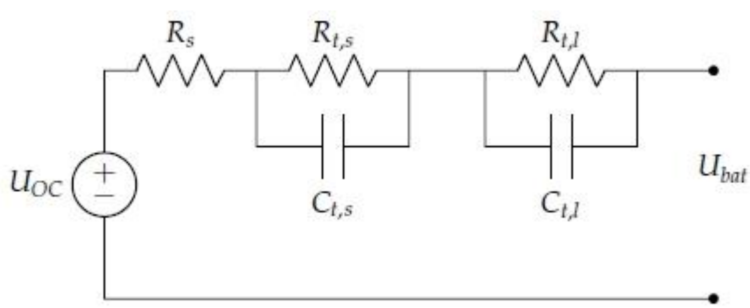
But in multiple studies more RC circuits (e.g, 2 RC circuits in Figure 2.6b) can be added to improve accuracy and model long-term dynamics [36]. To take DC response or battery runtime into account, additional components can be added to the model, but not both if implementation is made in circuit simulators [37]. Also, it was found that circuit components are dependant on SoC with nearly constant values for 20 % - 80 % and change exponentially within 0 % - 20 % of SoC.[36].

The most frequent way[36], [37] for SoC calculation is by the use of the Ampere-Hour integral (Coulomb counting) method, which requires knowledge of inital SoC level. This method is based on the charge value that has been transferred into or out of the battery.

$$SoC = SoC_0 - \frac{1}{Q_{us}} \int I_{bat}(t)dt \qquad (2.1)$$



2 (a) RC circuit



2 (b) RC circuit

Figure 2.6 Thevenin-based model ; (A) RC circuit, (B) R,C circuit

Where:

S_0C_0- Initial SOC

Further in [36] the researches show the dependence on temperature by Arrhenius relation 2.2 and high current values for long term transient resistance.

$$A = A_{0.}e^{-\frac{E_a}{RT}} \qquad (2.2)$$

where A is quantity of interest, A_0 the pre-exponential term, E_a the activation energy, R the gas constant and T the temperature in Kelvin. However, in this work impact of using models at different temperatures is not important and can be neglected. To take into account an exponential behavior of voltage response with low SoC values, exponential term can be used, as shown in 2.3 [37].

$$R(SoC) = R_0 + k1.e^{k2.SoC} \qquad (2.3)$$

2.7 Supercapacitor modeling:

2.7.1 Definition of Super Capacitor:

A supercapacitor, an advanced form of the traditional capacitor, possesses an exceptional energy storage capacity, capable of holding hundreds of times more energy per unit volume or mass. This electrochemical device consists of two porous electrodes submerged within an electrolyte solution, enabling it to store charge electrostatically. The factors influencing its capacitance include the effective surface area of the electrodes, the separation distance between them, and the dielectric constant of the separator, much like a conventional capacitor.

While a conventional capacitor derives its surface area from flat, conductive plates, a supercapacitor derives its area from a porous carbon-based electrode material. This porous structure results in an extraordinarily high effective surface area compared to conventional flat plates. Consequently, it also maintains a minimal separation distance between these "plates." These combined attributes give rise to an exceptionally high capacitance when contrasted with a standard electrolytic capacitor.

In practical terms, supercapacitors exhibit capacitances ranging from 100 to 1000 times greater per unit volume in comparison to their conventional electrolytic counterparts [45].

Figure 2.7 The series bmod0140 supercapacitor

2.7.2 Modeling of the Supercapacitor:

The equivalent circuit used for conventional capacitors can also be applied to supercapacitors." Figure 2.8 shows the schematic circuit diagram as a representation of the first-order model for a supercapacitor given by [46].

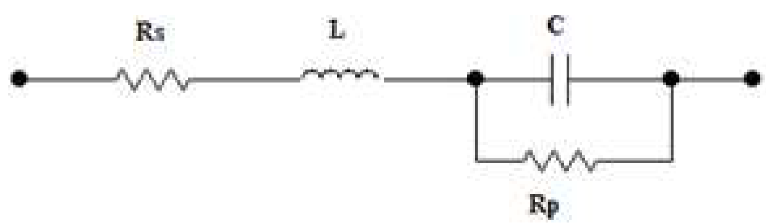


Figure 2.8 The first-order circuit model of a supercapacitor.

There are four ideal elements of the circuit given in figure 1, namely: a capacitance C, a series resistor R_S, a parallel resistor Rp , and a series inductor L. During charging and discharging, series resistance which is also called the equivalent series resistance (ESR) contributes to energy loss.

Leakage current resistance which is the parallel resistance Rp also takes energy loss due to capacitor self-discharge. In a practical capacitor Rp is always much higher than Rs, that is why Rp can be neglected particularly in high-power applications. A cell of a supercapacitor can be modeled using some standard circuit components as shown in figure 2.8 .

Chapter 03: Model Predictive Control for Battery Operation

3.1 Background Information

Control systems play a crucial role in achieving desired system responses by managing their outputs. There are two primary types of control systems: open-loop and closed-loop, also known as systems with no feedback and systems with feedback. The key distinction lies in feedback systems, where the controller not only has a reference input to achieve but also receives the system's output through a feedback loop, which adjusts the input. This feedback loop enhances controller stability by enabling it to adapt future inputs based on changes in the output, thus maintaining system performance. In contrast, open-loop systems can only predict the necessary input, making them less accurate and stable [38].

One of the most widely used controllers is the PID (Proportional-Integral-Derivative) controller, which falls under the category of closed-loop controllers. The PID controller makes corrections to the plant output using proportional, integral, and derivative terms. In practice, one or two components of the PID controller may be used by setting certain control gains to zero. Using proportional control alone for changing the reference value always results in some error since it requires an error to adjust the input. To address this limitation, the integral component integrates the error over time to eliminate any residual offset. On the other hand, the derivative component anticipates the future trend of the error, and sometimes it is omitted to enhance system robustness, especially in the presence of noisy data [39].

Batteries can be considered controlled objects as they often require controlled inputs during operation. For instance, controlling battery characteristics like State of Charge (SoC) or voltage is necessary to prevent misuse of Li-ion batteries within protection circuits [40]. Another application of battery control involves tracking and adjusting voltage and current based on the charging strategy. The most common charging strategy, constant-current/constant-voltage, involves charging the battery with a constant voltage until it reaches nominal voltage. Subsequently, it is charged while maintaining the nominal voltage until it is fully charged. Figure 3.1 illustrates typical current and voltage profiles. Knowing the desired current and voltage trajectories, a PI (Proportional-Integral) controller can be used for charging [41].

Model Predictive Control (MPC) has made a significant impact on industrial control engineering and has inspired extensive research. MPC offers several advantages over a conventional PID controller:

- It can handle systems with multiple inputs and outputs.
- It can easily impose constraints on inputs and state variables of the controlled object, providing greater flexibility in managing complex systems.

MPC's ability to handle complex control problems and incorporate constraints has contributed to its popularity in various applications, including battery control and energy management.

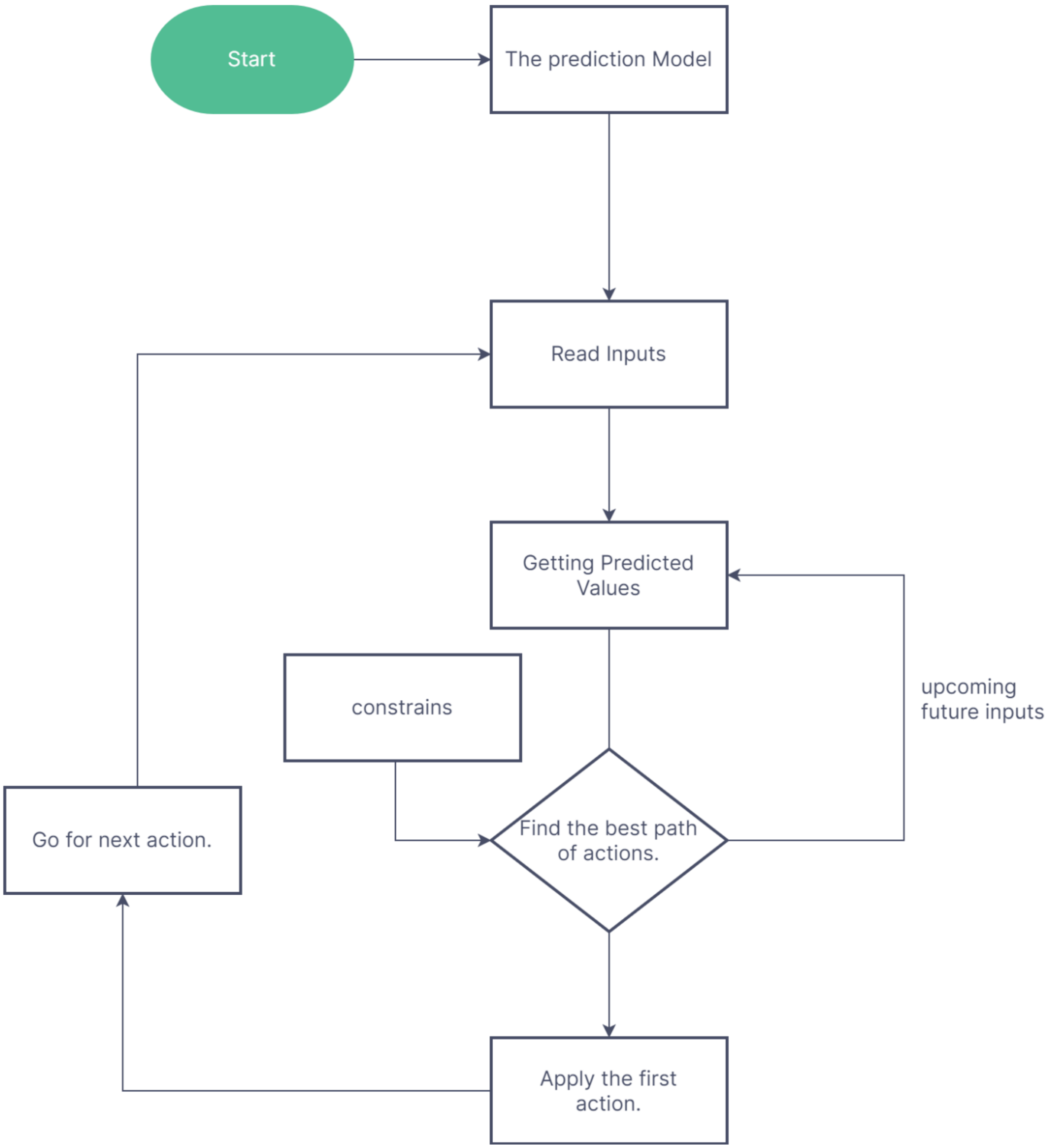


Figure 3.1 Flowchart basic algorithm of MPC

3.2 Utilizing MPC to Enhance Energy Storage Systems in Microgrid DC Environments:

Utilizing Model Predictive Control (MPC) in microgrid DC environments enhances energy storage systems (ESS) by optimizing DC-DC converters to regulate voltage and manage power distribution based on predictive models of energy generation and consumption. MPC ensures efficient energy flow and can dynamically manage battery state-of-charge (SoC) to balance load demands while preserving battery health. Moreover, it facilitates seamless grid interaction, deciding when to connect or disconnect from the main grid (islanding) based on real-time conditions, renewable energy availability, and load requirements. This comprehensive approach maximizes renewable energy integration, grid stability, and overall improving ESS.

3.2.1 system description:

The DC MICROGRID with energy storage system proposed in [41].

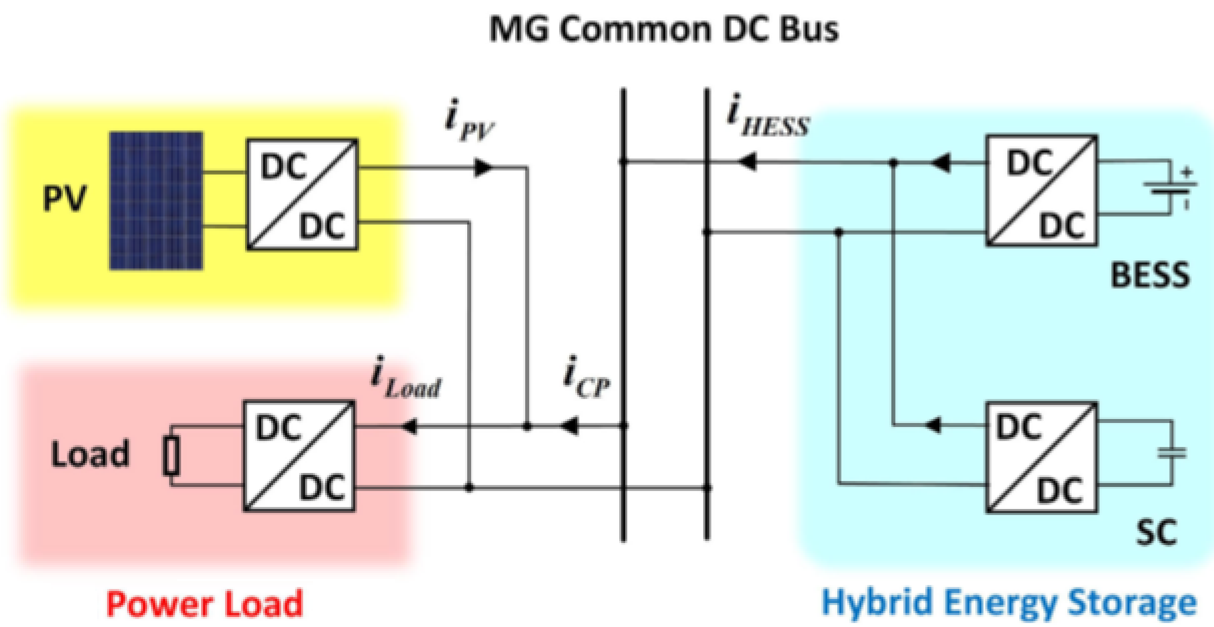


Figure 3.2 The schematic model of the case study system.

Figure 3.1 shows the schematic model of the case study, the system is an islanded DC microgrid that consists of a photovoltaic (PV) power generation system, a hybrid energy storage system (HESS) module, and a controllable power load (CPL). The HESS module comprises a battery energy storage system (BESS) and a supercapacitor (SC) connected in parallel. The PV system generates power that is fed into the DC bus through a DC-DC converter.

The HESS components will be controlled by the MPC strategy to regulate the power flow between the PV system, the BESS, and the SC, and to mitigate the effects of sudden load variations or rapid PV power fluctuations on the DC microgrid.

The schematic model is proposed in [41] and [42], the current and voltage sensors, the power electronics interfaces, and the communication links between the components. The model is used to simulate the dynamic behavior of the DC microgrid under different load change scenarios and to evaluate the performance of the MPC strategy.

The HESS module consists of a Battery Energy Storage System (BESS) and a Super Capacitor (SC), both connected in parallel to the DC bus of the microgrid through bidirectional boost converters. The CPL is treated as a DC load linked to the microgrid's DC bus via a power electronic converter, specifically a load converter. The CPL requires a consistent power supply, even when the voltage at the microgrid side fluctuates.

It is assumed that the PV system operates in Maximum Power Point Tracking (MPPT) mode and serves as a Constant Power Source (CPS). Additionally, the HESS functions as a grid-forming unit, playing a role in regulating the voltage of the DC bus within the microgrid.

A comparison between a hybrid storage system and a single storage system can be made in terms of several key factors. Here, we'll compare them in various aspects to understand their differences and potential advantages:

1. Energy Storage Capacity:

- Hybrid Storage System: A hybrid storage system typically combines two or more types of energy storage technologies, such as batteries and supercapacitors. This allows for a more extensive storage capacity and a wider range of capabilities.
- Single Storage System: A single storage system, such as a standalone battery, has a fixed storage capacity based on its design. It may have limitations in terms of scalability and the ability to handle various energy demands effectively.

2. Energy Density:

- Hybrid Storage System: Hybrid systems can potentially offer higher energy density because they can combine the high-energy density of batteries with the high power density of supercapacitors or other technologies.

- Single Storage System: Single storage systems might have varying energy density depending on the specific technology used. Batteries generally have good energy density but may not match the power density of other technologies.

3. Efficiency:

- Hybrid Storage System: Hybrid systems can be designed to optimize efficiency for specific use cases. By combining different storage technologies, they can enhance overall system efficiency by minimizing losses during charge and discharge cycles.
- Single Storage System: The efficiency of single storage systems can vary depending on the technology and the operating conditions. Batteries, for instance, can have different efficiencies at different states of charge and under various load conditions.

4. Cost:

- Hybrid Storage System: Hybrid systems may be more expensive to implement due to the cost of multiple storage technologies, additional control systems, and integration. However, they may provide better value in terms of performance and flexibility.
- Single Storage System: Single storage systems are generally simpler and may have lower upfront costs. However, their cost-effectiveness depends on the specific application and requirements.

5. System Reliability:

- Hybrid Storage System: Hybrid systems can enhance system reliability by providing redundancy and backup capabilities. If one storage technology fails or degrades, another can take over.
- Single Storage System: Reliability in single storage systems relies solely on the performance and durability of that particular technology. Failures or issues with the single system can lead to downtime.

6. Application Flexibility:

- Hybrid Storage System: Hybrid systems can be more versatile and adaptable to a wide range of applications, from grid energy storage to electric vehicles. They can balance the strengths of different technologies to meet specific needs.
- Single Storage System: Single systems are typically designed for specific applications. Adapting them to different use cases may require additional modifications or compromises.

In summary, the choice between a hybrid storage system and a single storage system depends on the specific requirements and goals of the application. Hybrid systems offer greater flexibility, efficiency optimization, and reliability but come at a potentially higher cost. Single storage systems are simpler and more cost-effective for certain applications but may not provide the same level of versatility and performance optimization. The decision should be made based on the unique demands of the project or system.

3.2.3 Modeling of the system :

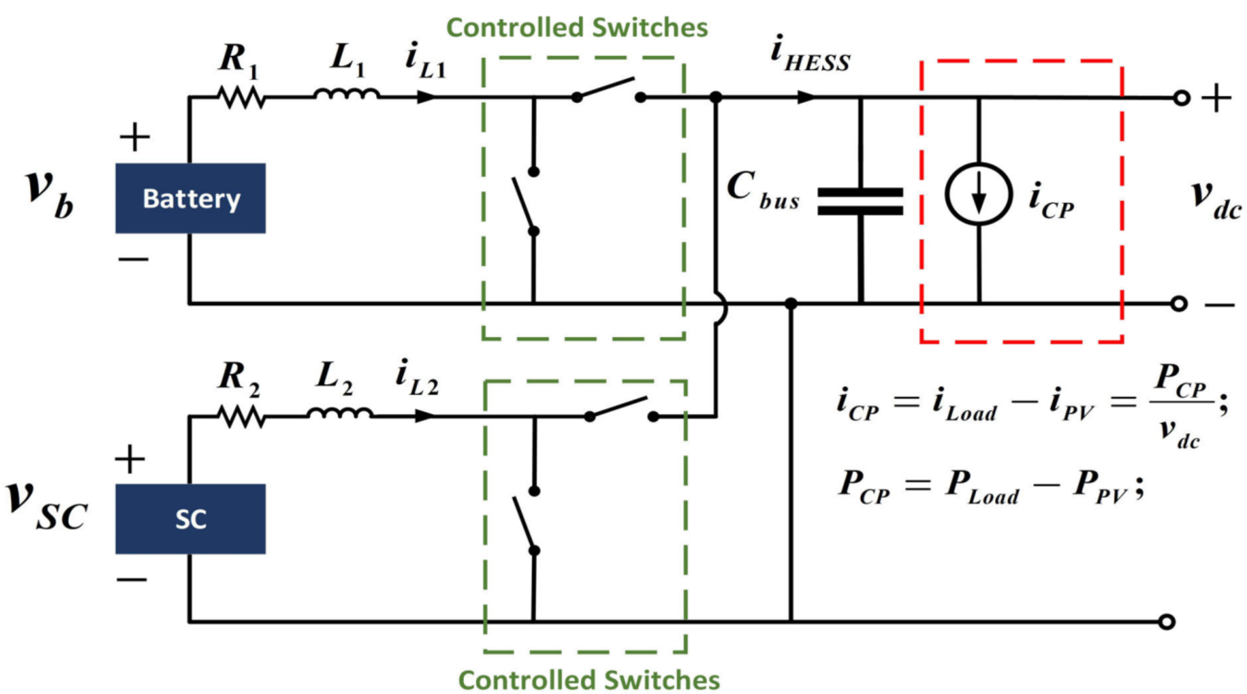


Figure 3.3 The circuit model of the case study DC MG system.

Using the circuit model presented in Figure. 3.3 and the dynamic equations for single-bus DC Microgrids (MGs) with Constant Power Loads (CPLs) as proposed in Stability enhancement based on virtual impedance for DC microgrids [41].

specifically, the islanded single-bus DC MG, as follows:

$$\begin{cases} L_1 \dfrac{di_{L1}}{dt} = v_b - R_1 i_{L1} - v_{dc}(1-d_1) \\ L_2 \dfrac{di_{L2}}{dt} = v_{SC} - R_2 i_{L2} - v_{dc}(1-d_2) \\ C_{bus} \dfrac{dv_{dc}}{dt} = i_{L1}(1-d_1) + i_{L2}(1-d_2) - \dfrac{P_{CP}}{v_{dc}} \end{cases}$$

………………..[42]

Where C_{bus} is the total capacitance of the MG DC bus. $d_1$and $d_2$are the duty cycle of the BESS and SC boost converters that are calculated by the PI current regulators. $P_{CP}$is also the difference between the generated power by the CPL and CPS (e.i, $P_{CP} = P_{Load} - P_{PV}$). [51].

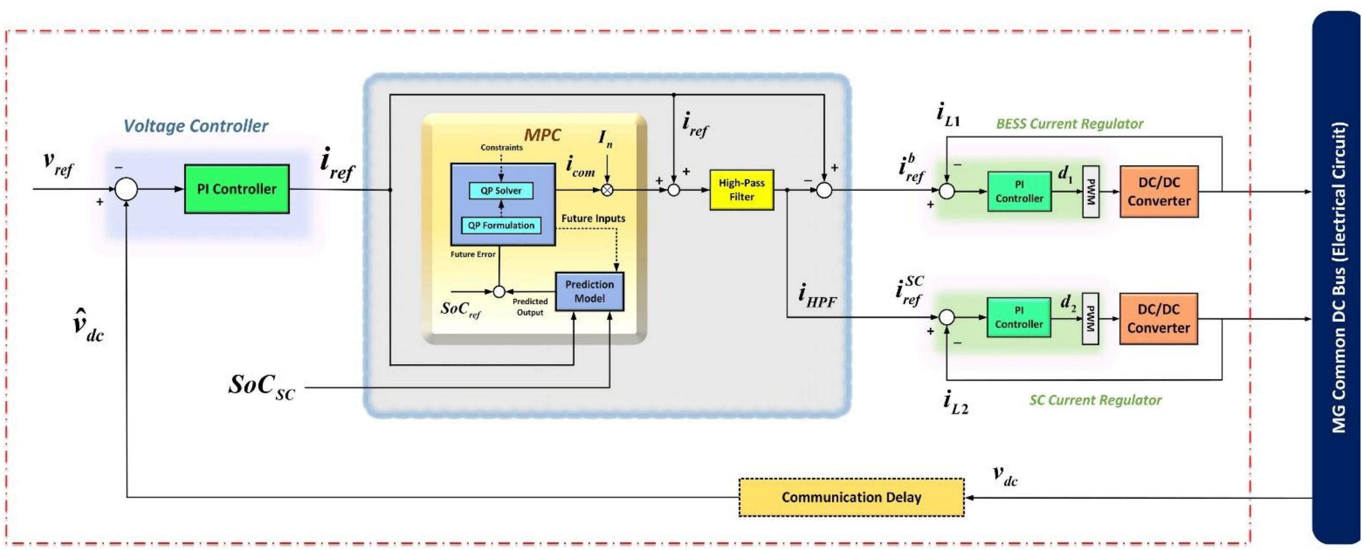


Figure 3.4 MPC structure [42].

- MPC Technique in Figure 3.4: The figure illustrates the MPC technique.
- Voltage Controller: like a conventional, the voltage controller at the primary control layer of the MG computes a reference current to regulate the MG common DC bus voltage.

- Continuous Operation: The MPC module ensures the continuous operation of the SC and filter.
- SoC Regulation: The MPC module regulates the State of Charge (SoC) of SC to a reference value while considering the SoC constraints of the SC.
- Predictive Control: At each time step, the MPC controller employs the discretized dynamical model to predict the future error in SoC within a moving horizon (prediction horizon).
- Minimizing Error: To minimize the error, it computes a sequence of compensation currents within a control horizon and applies the first one.
- Compensation Term: Based on the SoC variation of SC and the HESS reference current, the MPC compensator sends a compensation term to the HPF.
- Coordination between BESS and SC: After passing through the HPF, the compensation term is added to the reference current of the SC and subtracted from the reference current of the BESS, providing additional coordination between them.
- Control of SoC Variation: The proposed MPC technique controls the SoC variation within a predefined range.
- Continuous Operation Assurance: This ensures the continuous operation of the SC and filter.
- Detailed Sections: Subsequent sections provide details on the prediction model, MPC objective function, tuning parameters, functionality of the MPC compensator, and the dynamic stability of the MG under the proposed MPC approach.

3.3 Strategy for simulations:

To show the efficiency of the proposed MPC technique in improving the performance of the Storage system, the following steps were taken in the simulation:

Two test cases were considered:

Case 1, which uses a conventional strategy, and Case 2, which employs the MPC technique.

For both cases, the BESS is a Lithium-Ion type, and the SC consists of an ideal capacitor with a series internal resistance. It is assumed that the SC has no leakage current. Also, it is assumed that the HESS components and PV are efficiently sized.

Overall, the simulation results demonstrate the effectiveness of the proposed MPC technique in improving the performance of the BESS in DC microgrids.

Subjecting the system to Three scenarios of stress at storage system, The purpose of these scenarios is to evaluate the performance of the MPC in regulating the power flow between the battery energy storage system and the supercapacitor energy storage system during sudden load variations. The scenarios also help to assess the effectiveness of the proposed control strategy in restoring the state of charge (SoC) of the supercapacitor energy storage system to its reference value after a sudden load variation.

3.4 Simulation results:

3.4.1 Evaluating Control Strategy Performance in Dynamic Load Scenarios for DC Microgrids:

Three different load change scenarios that are used in the simulation to evaluate the performance of the proposed control strategy. These scenarios are:

- Scenario 1: This scenario involves a sharp shift of power demand from 10 kW to 15 kW at t = 10 s, followed by a sharp reduction from 15 kW to 10 kW at t = 25 s. This scenario represents a sudden load variation that can cause stress on the energy storage systems and affect the stability of the DC microgrid.
- Scenario 2: This scenario involves a fast and periodic pulsed shape variation of power demand. This scenario represents the effect of pulsed power loads (PPLs) such as electric propulsion or laser guns on the DC microgrid.
- Scenario 3: This scenario involves a sharp increase of power demand from 10 kW to 19 kW at t = 70 s, followed by a sharp decrease from 19 kW to 10 kW at t = 90 s. This scenario represents the effect of adding or losing a load/source converter on the DC microgrid.

3.4.2 Visualizing Load Change Scenarios and Power Demand Profiles for Control Strategy Evaluation:

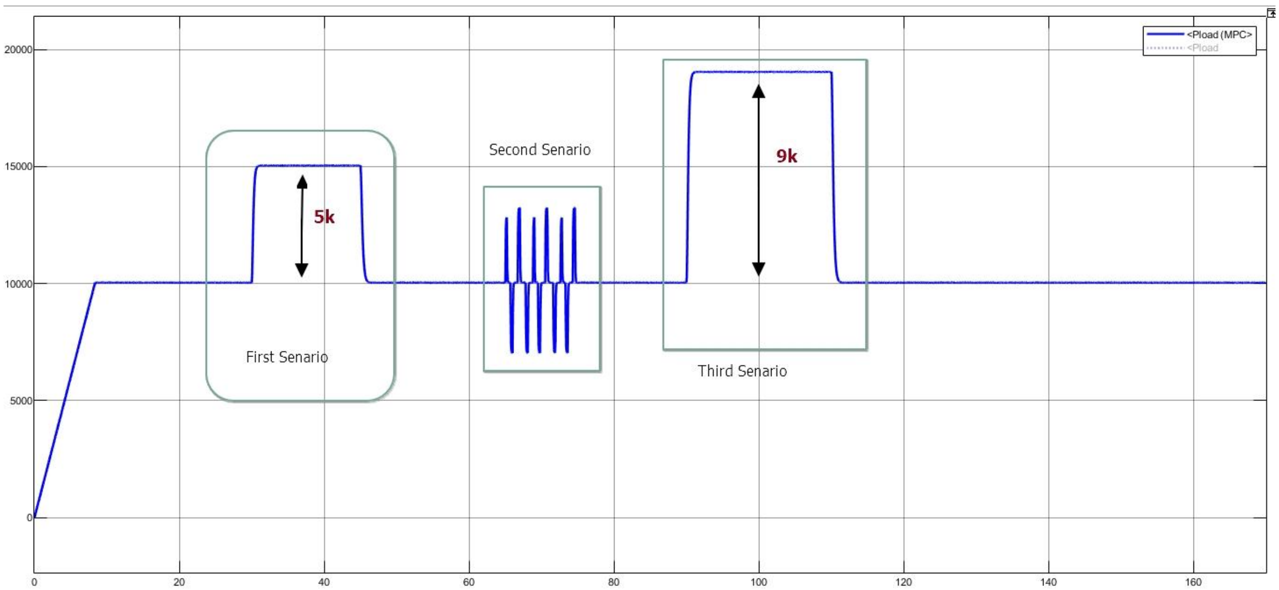


Figure 3.5 The load change scenarios in the test systems.

The figure 3.5 shows the power demand profile for each load change scenario, which represents the amount of power required by the load at each time step. The time axis represents the duration of each load change scenario, and the power level at which the load changes occur is indicated by the vertical dashed lines. The purpose of this figure is to provide a visual representation of the load change scenarios used in the simulation to evaluate the performance of the MPC .

3.4.3 Comparative Analysis of Control Strategies for Supercapacitor and Battery Energy Storage Systems in Dynamic Load Scenarios:

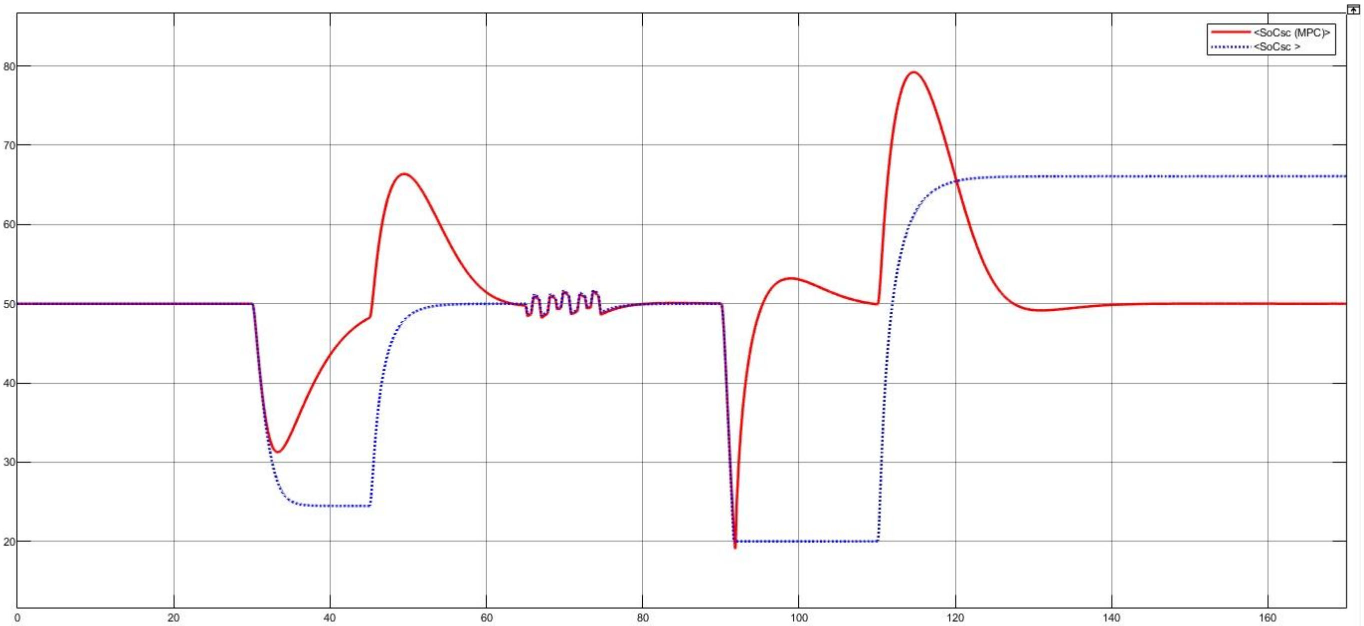


Figure 3.6 SoC of SC during laod change behave with MPC (red) conventional (Blue)

In Figure 3.1. the main keys are:

- The x-axis represents the simulation time in seconds.
- The y-axis represents the State of Charge (SoC) of the supercapacitor (SC) in percentage.
- The blue line represents the SoC of SC in the conventional strategy (Case 1).
- The red line represents the SoC of SC in the proposed MPC technique (Case 2).

Discussion:

Figure 3.6, it shows In the first scenario, a sudden load shift from 10 kW to 15 kW at t = 10 s and a subsequent reduction to 10 kW at t = 25 s lead to a significant power flow change between the PV system, BESS, and SC. Under the conventional strategy, the SC's SoC declines to its minimum allowed value at t = 23.5 s. In contrast, the MPC strategy effectively maintains the SC's SoC within the desired range throughout this period. The BESS SoC decreases in both strategies, but MPC provides a smoother and more gradual change in BESS output power, thereby reducing stress on both BESS and DC microgrid voltage control.

In the second scenario, periodic pulsed-shape load variations create power flow fluctuations among the PV system, BESS, and SC.

MPC method excels in regulating power flow and keeps the SC SoC within the desired range. Conversely, the conventional strategy exhibits more significant variations in the SoC of SC .

The third scenario involves a sudden load increase from 10 kW to 19 kW at t = 70 s and a subsequent reduction to 10 kW at t = 90 s, causing substantial power flow changes. MPC efficiently SC, ensuring that their SoC remains within the desired range. In contrast, the conventional strategy results in greater variations in SC SoC.

Conclusion:

In conclusion, Figure 3.6 provides a clear visual representation of the effectiveness of the proposed Model Predictive Control (MPC) strategy (Case 2) compared to conventional feedback control (Case 1) in managing the State of Charge (SoC) of the supercapacitor (SC) and the battery energy storage system (BESS) during dynamic load scenarios. The SoC variation is crucial for the stability and performance of energy storage systems in microgrids. In Case 1, the conventional strategy fails to prevent a significant drop in the SoC of the SC after sudden load changes, indicating its limitations in handling rapid power fluctuations. In contrast, Case 2, employing MPC, demonstrates superior performance by maintaining the SoC of the SC within the predefined range even during challenging load variations. This result underscores the efficacy of the MPC strategy in coordinating the SC and BESS, ensuring stable power flow regulation, and safeguarding the SoC of the SC. Numerical thresholds are not included in Figure 16; instead, it offers a graphical representation of the critical SoC dynamics and their correlation with the control strategies and time.

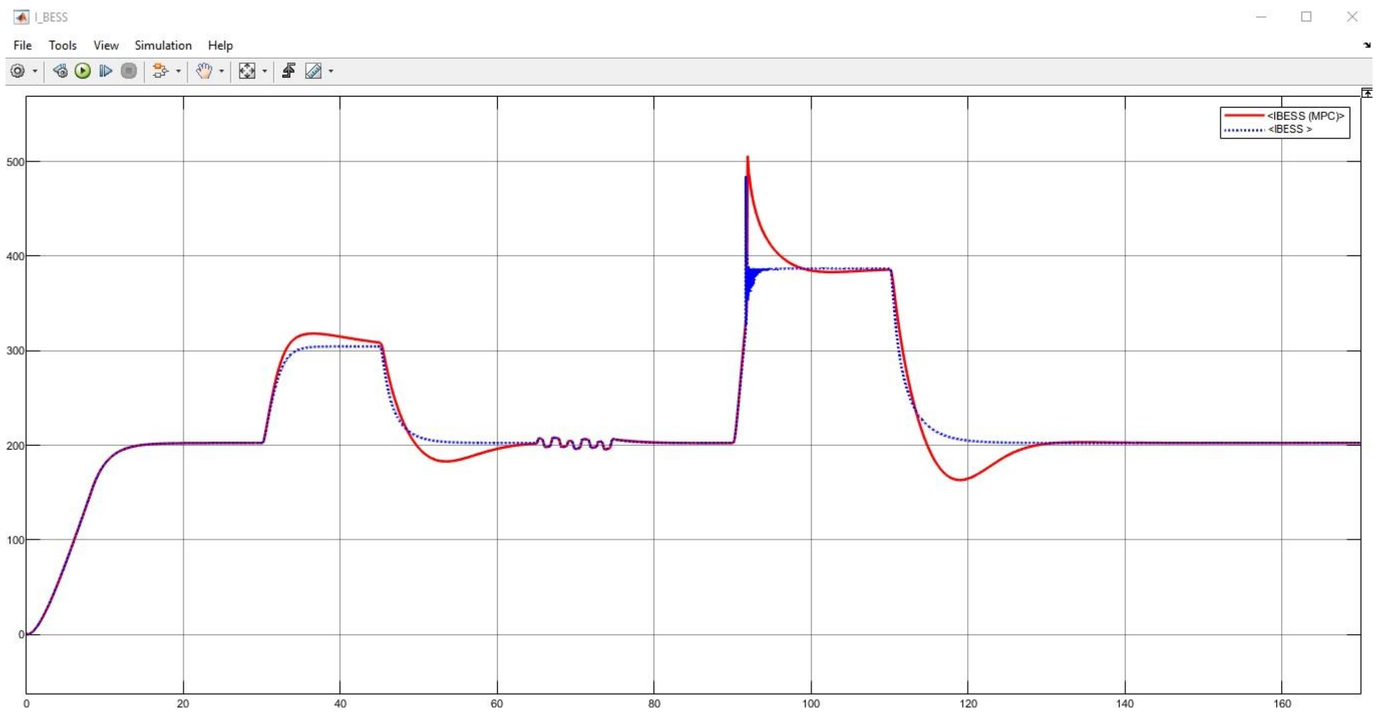


Figure 3.7: (a)Analyzing BESS Currents (I_BESS)

Discussion: The BESS current represents the current flowing through the battery energy storage system (BESS). The figure shows that in Case 1, the BESS current is relatively stable and follows the reference current (i.e., iref) closely. However, in Case 2, the BESS current is more erratic and deviates significantly from the reference current. This indicates that the current allocation system in Case 1 is more effective in regulating the BESS current and maintaining stability in the microgrid. The authors discuss the importance of effective current allocation systems in microgrids, as they play a crucial role in maintaining stability and reliability in the system.

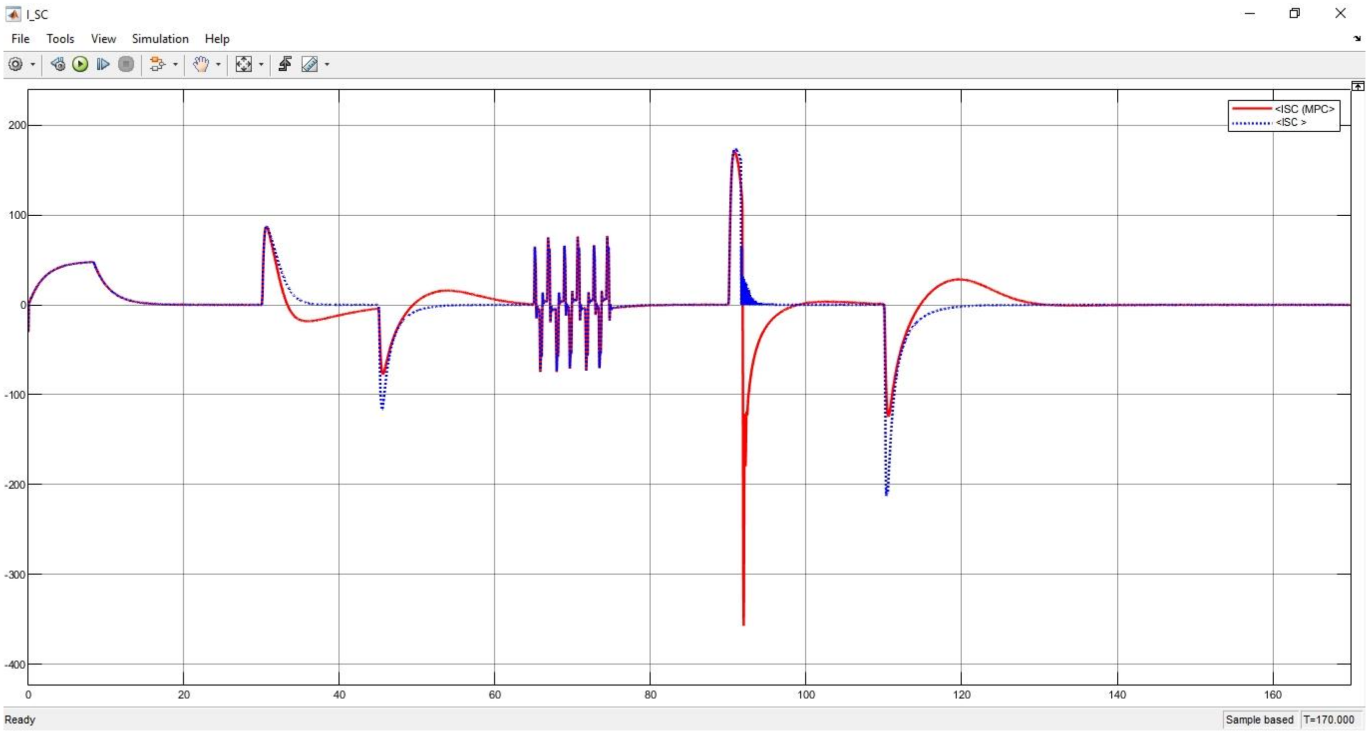


Figure 3.7: (b) Analyzing SC Currents (I_SC)

Discussion: The SC current represents the current flowing through the supercapacitor (SC) energy storage system. The figure shows that in both cases, the SC current is relatively stable and follows the reference current (i.e., iref) closely. This indicates that the current allocation system is effective in regulating the SC current and maintaining stability in the microgrid. The authors discuss the advantages of using SCs in microgrids, such as their high power density, fast response time, and long cycle life. They also note that SCs can complement other energy storage technologies, such as battery energy storage systems (BESS), to provide a more reliable and efficient energy storage solution for microgrids.

In the two Figures the main keys are:

- The x-axis represents the simulation time in seconds.

- The y-axis represents the SC and BESS currents (i.e., i_BESS,i_SC) in Amperes.

- The blue line represents the conventional (Case 1).

- The red line represents the proposed MPC technique (Case 2).

Figure 3.7(a) shows the HESS reference current for both control strategies. It can be observed that the MPC strategy provides a more accurate and stable tracking of the reference current compared to the conventional feedback control strategy. Figure 3.7(b) shows the SC and BESS currents for both control strategies. It can be observed that the MPC strategy provides a better coordination between the SC and BESS, which results in a smoother and more balanced power flow between the two energy storage systems. In contrast, the conventional feedback control strategy shows a more erratic and unbalanced power flow between the SC and BESS, which can lead to instability and reduced performance of the microgrid. Regarding the effect of the three scenarios on the performance of the current allocation systems, showing the performance of the current allocation systems in the case study microgrids for both control strategies using Figure 3.7. This figure shows the HESS reference current and the SC and BESS currents for both control strategies, which can be used to evaluate the performance of the systems under different load conditions. MPC strategy is effective in regulating the power flow and maintaining the stability of the microgrid compared to the conventional feedback control strategy, even during sudden load changes.

Therefore, from Figure 3.7 it is seen that related to the improvement of HESS performance in DC microgrids. The MPC can effectively improve the performance of HESS by regulating the power flow and maintaining the stability of the microgrid, which can lead to increased efficiency, reliability, and lifespan of the HESS.

Conclusion:

Regulating the power flow between the SC and BESS while maintaining the SC's State of Charge (SoC) within an acceptable range, even during sudden load changes. In contrast, the conventional feedback control strategy struggles to maintain stability during such events, leading to potential microgrid instability and performance degradation.

While specific numerical thresholds for these scenarios are not provided, Figure 3.7 illustrates the performance of current allocation systems for both control strategies. It showcases the FB-MPC strategy's ability to track HESS reference current accurately and maintain a balanced power flow between the SC and BESS, in contrast to the erratic and unbalanced behavior observed in the conventional feedback control strategy.

In essence, Figure 3.7 directly relates to the enhancement of HESS performance within DC microgrids. The FB-MPC strategy effectively improves HESS performance by regulating power flow, ensuring stability, and potentially increasing efficiency, reliability, and lifespan of the HESS. Overall, this research demonstrates the practical advantages of adopting the FB-MPC approach in enhancing microgrid energy management and stability, especially under challenging load change scenarios.

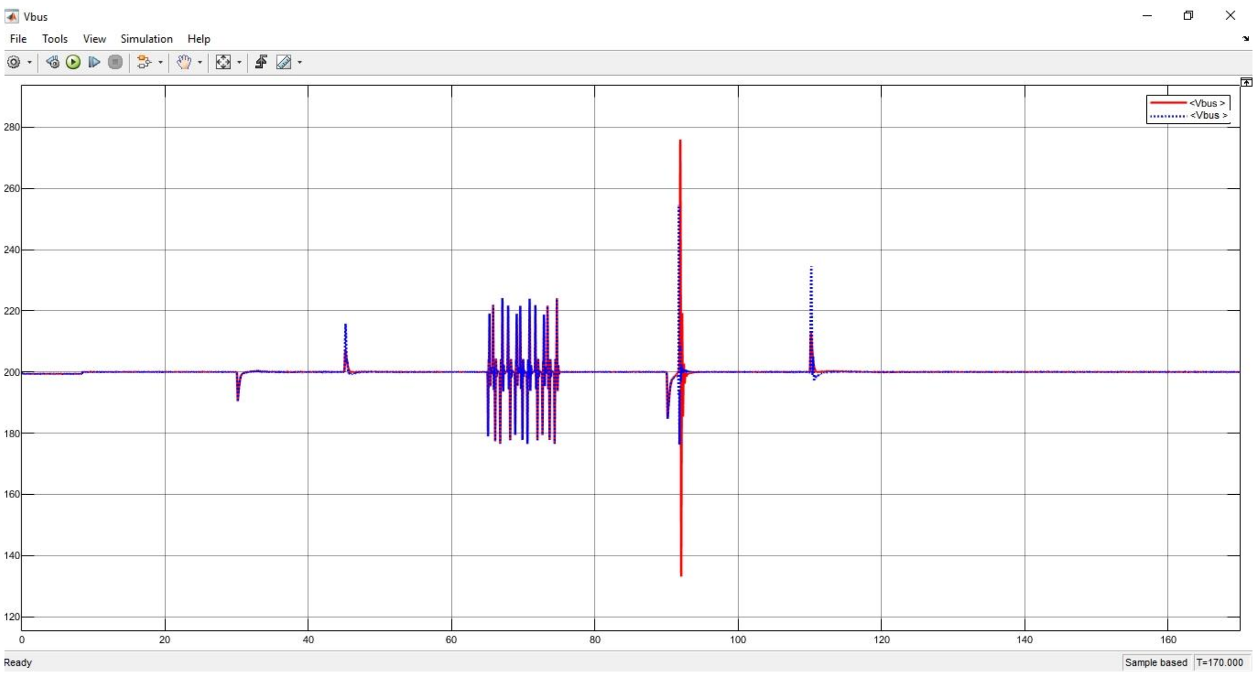


Figure 3.8 .Voltage buss under load fluctuations scenarios

Discussion:

The figure illustrates the voltage of the DC microgrid during the three scenarios for both the conventional strategy and the MPC.

In the first scenario, the sudden load shift from 10 kW to 15 kW at t = 10 s and the subsequent load reduction from 15 kW to 10 kW at t = 25 s cause a significant voltage sag in the DC bus in the conventional strategy, while the MPC strategy provides a smoother and smaller voltage sag.

In the second scenario, the periodic pulsed-shape variation of the load power causes a fluctuation in the DC bus voltage, but the MPC strategy provides a better regulation of the voltage and maintains it within the desired range, while the conventional strategy shows a larger variation in the voltage.

In the third scenario, the sudden load increase from 10 kW to 19 kW at t = 70 s and the subsequent load reduction from 19 kW to 10 kW at t = 90 s cause a significant voltage sag in the DC bus in the conventional, while the MPC strategy provides a smoother and smaller voltage sag.

Conclusion :

The comparative analysis of the voltage profiles in a DC microgrid under three distinct scenarios reveals the clear advantages of employing Model Predictive Control (MPC) over conventional strategies. In the first scenario, MPC mitigates the substantial voltage sag resulting from load fluctuations, providing a more stable and controlled response. Similarly, in the second scenario characterized by periodic load variations, MPC excels in maintaining voltage within the desired range, outperforming conventional methods. Lastly, in the third scenario with sudden load changes, MPC once again demonstrates its ability to minimize voltage sag and ensure a smoother operation. These findings underscore the effectiveness of MPC in enhancing the reliability and stability of DC microgrids, making it a valuable choice for advanced energy management systems.

3.5 General Conclusion:

In conclusion the model predictive control (MPC) strategy to regulate the power flow between the photovoltaic (PV) power generation system, the battery energy storage system (BESS), and the supercapacitor (SC) in an islanded DC microgrid. The MPC strategy utilizes the dynamical model of the system to predict the system's outputs within a moving horizon and then computes a sequence of future control actions to minimize a predefined cost function. The results of the simulation model show that the proposed MPC strategy provides a better regulation of the power flow and a smoother and more gradual change in the output power of the HESS components, which reduces the stress on the components and improves the dynamic stability of the DC microgrid under sudden load variations or rapid PV power fluctuations. The MPC strategy also reduces the voltage sag in the DC bus and improves the voltage quality of the DC microgrid. The MPC strategy provides a promising approach to power and current in battery-supercapacitor hybrid energy storage systems for DC microgrids. The strategy can improve the dynamic stability, reliability, and voltage quality of the DC microgrid under sudden load variations or rapid PV power fluctuations. The MPC strategy is a powerful tool for directly applying operational constraints in real-time optimization and can automatically limit the state of charge (SoC) variation of the storage system components in a predefined range. However, it has considerably higher computational complexity compared to the conventional approaches.

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