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Application of Model Predictive Control

Presented by
- Nouiri Mohammed Elmehdi
- Ziane Oussama

Proposed by :
PR. Sebaa Karim

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Abstract

This thesis explores the application of advanced control strategies to enhance the stability and performance of a three-area power system. Specifically, we investigate the efficacy of Linear Model Predictive Control (LMPC), Neural Network Predictive Control (NNPC), and Adaptive Model Predictive Control (AMPC) in addressing the challenges associated with multi-area power systems. The LMPC method is employed to provide a baseline control performance by utilizing a linear model of the power system. This approach is benchmarked against more sophisticated techniques to highlight its advantages and limitations. Following this, NNPC is introduced, leveraging the capabilities of neural networks to capture the nonlinear dynamics of the power system more accurately. The predictive control strategy is enhanced through the use of a trained neural network model, enabling improved handling of system uncertainties and nonlinearity. Finally, the AMPC approach is implemented, which dynamically adjusts the model and control parameters in response to real-time system changes. This adaptive strategy is particularly effective in dealing with variations in system dynamics and operating conditions, ensuring robust and resilient performance. Through extensive simulation studies and comparative analysis, the results demonstrate that while LMPC provides a solid foundation, NNPC and AMPC significantly outperform in terms of accuracy, adaptability, and overall system stability. The findings underscore the potential of neural network-based and adaptive control strategies in modern power system management, paving the way for their integration into practical applications. This thesis contributes to the field by offering a comprehensive analysis of these advanced predictive control techniques, providing valuable insights into their practical implementation and benefits for enhancing multi-area power system operations.

key words : Linear Model Predictive Control. Neural Network Predictive Control. Adaptive Model Predictive Control

Résumé

Le but de notre travail c'est explorer l'application de stratégies de contrôle avancées pour améliorer la stabilité et les performances d'un système électrique à trois zones. Plus précisément, nous étudions l'efficacité du la command prédictif linéaire (LMPC), du command prédictif par réseau de neurones (NNPC) et du la command prédictif adaptatif (AMPC) pour relever les défis associés aux systèmes électriques multi-zones. La méthode LMPC est utilisée pour fournir une performance de contrôle de base en utilisant un modèle linéaire du système électrique. Cette approche est comparée à des techniques plus sophistiquées pour mettre en évidence ses avantages et ses limitations. Ensuite, le NNPC est introduit, tirant parti des capacités des réseaux de neurones pour capturer plus précisément la dynamique non linéaire dusystème électrique. La stratégie de contrôle prédictif est améliorée grâce à l'utilisation d'un modèle de réseau de neurones entraîné, permettant une meilleure gestion des incertitudes et des non-linéarités du système. Enfin, l'approche AMPC est mise en œuvre, ajustant dynamiquement le modèle et les paramètres de contrôle en réponse aux changements en temps réel du système. Cette stratégie adaptative est particulièrement efficace pour gérer les variations de la dynamique du système et les conditions de fonctionnement, garantissant une performance robuste et résiliente. À travers des études de simulation approfondies et une analyse comparative, les résultats montrent que bien que le LMPC fournisse une base solide, le NNPC et l'AMPC offrentdes performances nettement supérieures en termes de précision, d'adaptabilité et de stabilité globale du système. Les résultats soulignent le potentiel des stratégies de contrôle basées sur les réseaux de neurones et adaptatives pour la gestion moderne des systèmes électriques, ouvrant la voie à leur intégration dans des applications pratiques.

Le travail contribue au domaine en offrant une analyse complète de ces techniques de contrôle prédictif avancées, fournissant des information précieux pour leur mise en œuvre pratique et leurs avantages pour l'amélioration des opérations des systèmes électriques multi-zones.

Mots clés : la command predictive lineair.la command prédictif par réseau de neurons. command prédictif adaptatif

ملخص

تستكشف هذه الأطروحة تطبيق استراتيجيات التحكم المتقدمة لتحسين استقرار وأداء نظام طاقة يتكون من ثلاث مناطق. نحقق تحديدًا في فعالية التحكم التنبؤي بالنموذج الخطي(LMPC) ، والتحكم التنبؤي بالشبكة العصبية(NNPC) ، والتحكم التنبؤي بالنموذج التكيفي (AMPC) في مواجهة التحديات المرتبطة بأنظمة الطاقة متعددة المناطق. يُستخدم أسلوب LMPC لتوفير أداء تحكم أساسي باستخدام نموذج خطي لنظام الطاقة. تم مقارنة هذا النهج مع نهجين أكثر تطورًا لتسليط الضوء على مميزاته وعيوبه. بعد ذلك، يتم تقديم NNPC الذي يستفيد من قدرات الشبكات العصبية اللتقاط الديناميكيات غير الخطية لنظام الطاقة بدقة أكبر. يتم تعزيز استراتيجية التحكم التنبؤي من خلال استخدام نموذج شبكة عصبية مدربة، مما يسمح بتحسين التعامل مع عدم اليقين في النظام والاال خطية. أخيرًا، يتم تنفيذ نهج AMPC الذي يعدل النموذج ومعلمات التحكم ديناميكيًا استجابةً للتغيرات في النظام في الوقت الفعلي. هذه الاستراتيجية التكيفية فعالة بشكل خاص في التعامل مع التغيرات في ديناميكيات النظام وظروف التشغيل، مما يضمن أداءً قويًا ومرنًا. من خلال دراسات محاكاة واسعة النطاق وتحليل مقارن، تُظهر النتائج أنه في حين يوفر LMPC أساسا قويًا، فإن AMPC AMPC يتفوقان بشكل كبير من حيث الدقة والتكيف والاستقرار العام للنظام. تؤكد النتائج على إمكانيات استراتيجيات التحكم القائمة على الشبكات العصبية والتكيفية في إدارة أنظمة الطاقة الحديثة، مما يمهد الطريق لدمجها في التطبيقات العملية.

تساهم هذه الأطروحة في هذا المجال من خلال تقديم تحليل شامل لهذه التقنيات التنبؤية المتقدمة، وتقديم رؤى قيمة حول تنفيذها العملي وفوائدها لتحسين عمليات أنظمة الطاقة متعددة المناطق.

كلمات مفتاحية : تحكم تنبؤي بالنموذج الخطي . تحكم تنبؤي بالشبكة العصبية. : تحكم تنبؤي بالنموذج التكيفي

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List of Symbols

$\boldsymbol{\Delta f}$: is the deviation from the nominal frequency f_s.

$\boldsymbol{\Delta P_m}$: the total change in mechanical power.

$\boldsymbol{\Delta P_{\dot{L}}}$: the electrical power imbalance.

$\boldsymbol{\Delta P_{\text{tie}}}$: the change in total power flow from area i on all its tie lines.

$\boldsymbol{H}$:the inertia of the rotating masses.

$\boldsymbol{D^i}$ the load damping coefficient of the area.

$\boldsymbol{\Delta \bar{f}^{i}}$: is the local frequency in area i/j

$\boldsymbol{T_i}$:the synchronizing torque coefficient between area i and j.

:the number of areas of the system.

$\boldsymbol{\Delta P_c}$ is the control signal to the governor.

$\boldsymbol{\Delta P_g}$: the valve position from the governor to the turbine,

$\boldsymbol{T_g}$: the time constants of the governor

$\boldsymbol{\Delta P}$:the mechanical power output from the turbine.

$\boldsymbol{T}$:the time constants of the turbine

$(\boldsymbol{t})$ is the control input vector (e.g., control signals to the generators u_1, u_2).

$(\boldsymbol{t})$ represents disturbances such as load changes.

$(\boldsymbol{t})$ is the output vector.

$\boldsymbol{A}, \boldsymbol{B}$, and $\mathbf{C}$, $\boldsymbol{E}$ are system matrices.

$u_M(k)$ is called the vector of measured disturbances, i.e. input signals that are not calculated by the controller,

$\boldsymbol{x_k}$ is the state vector at time step

$\mathbf{k}$, and $\boldsymbol{u_k}$ is the control input.

$(\boldsymbol{x_i} + \boldsymbol{u_i})$ denotes the stage cost at each time step

$\emptyset(\boldsymbol{x_k} + \boldsymbol{N})$ represents the terminal cost at the end of the prediction horizon.

$\boldsymbol{\lambda_P}$ is the weighting coefficient

N is the prediction horizon.

$x_{re}(k)$ is the reference state vector.

GENERAL INTRODUCTION

The modern power system is an intricate and dynamic network designed to generate, transmit, and distribute electrical energy reliably and efficiently. As the demand for electricity continues to grow, alongside the integration of renewable energy sources, the stability and control of power systems have become increasingly critical. This necessitates advanced control strategies to ensure that power systems operate within safe and optimal parameters.

In this context, the Load Frequency Control (LFC) is a fundamental aspect of power system operation, aimed at maintaining the system frequency within specified limits and ensuring the balance between power supply and demand. This thesis focuses on the analysis and implementation of various control strategies for LFC in a three-area power system. Specifically, it delves into Linear Model Predictive Control (LMPC), Neural Network Model Predictive Control (NNPC), and Adaptive Model Predictive Control (AMPC), providing a comparative study of their performance and effectiveness.

A three-area power system is a simplified representation of a larger interconnected power grid, where each area can be considered as a control zone with its own generation and load characteristics. These areas are interconnected through tie-lines, allowing the exchange of power to maintain system stability. The control of frequency and tie-line power flows in such a multi-area system is a complex task due to the interactions between the areas and the inherent time delays in the system.

LMPC is a control strategy that uses a linearized model of the power system to predict future behavior and optimize control actions over a finite horizon. It is known for its robustness and ability to handle multi-variable control problems with constraints. NNPC extends the principles of LMPC to neural network aplications on systems. Given that power systems exhibit NN system identification and estimation , NNPC can learn and br trained to provide more accurate predictions and improved performance over other approaches. It, however, involves more complex computations.while in the other hand , AMPC introduces adaptability into the predictive control framework, allowing the controller to update its model parameters in real-time based on observed system behavior. This adaptability makes AMPC particularly useful in dealing with system uncertainties and changing operating conditions.

Our primary objective is to design, implement, and compare LMPC, NNPC, and AMPC for LFC in a three-area power system. The comparative analysis aims to highlight the strengths and weaknesses of each control strategy in terms of stability, robustness, computational efficiency, and practical applicability. The thesis also seeks to contribute to the body of knowledge in power system control by providing insights into the suitability of advanced predictive control methods in maintaining power system stability. The thesis is structured as follows:

Chapter one provides a comprehensive overview of power system operation, the importance of load frequency control, and the challenges involved in multi-area power systems.the modeling of three area power system and its schematics. while in Chapter two reviews the theoretical foundations of model predictive control, including linear approaches, as well as the principles of LMP control.

Chapter three details the methodology used for the design and implementation of NNPC for a three-area power system, including system modeling, control design, and simulation setup. Chapter four discusses the findings, implications, theoretical study on the application of AMPC for two areas power system.

Chapter five presents the simulation results, offering a comparative analysis of the three control strategies in terms of their performance metrics.

By exploring and evaluating these advanced control strategies, this thesis aims to enhance the understanding of effective LFC mechanisms in multi-area power systems and to propose solutions that can be implemented to achieve more reliable and efficient power system operations.

Chapter I

Structure and modeling of power system

I. Chapter I: Structure and modeling of power system

I.1 Introduction:

Maintaining constant frequency in a power system is crucial for stable operation and equipment protection. Deviations from nominal frequency can lead to significant issues, including reduced equipment lifespan, fluctuating motor speeds, and overall system unreliability. These frequency variations arise from imbalances between power generation and load demand, necessitating precise control mechanisms to ensure system stability.

This chapter delves into the principles of power system frequency control within a three-area model, providing a comprehensive analysis of how generation and load imbalances affects on system frequency. By examining this model, we can better understand the dynamics of frequency deviations and the interdependencies between different areas of the power system. We will discuss the primary factors contributing to these imbalances, including sudden load changes, generation outages, and the inherent variability in renewable energy sources.in addition, we will go through the modulation process of the system.

Moreover, the chapter explores various control strategies employed to maintain frequency stability. These include automatic control error (ACE). Each control strategy will be evaluated in terms of its effectiveness, implementation challenges, and potential improvements.

Through detailed case studies and simulations, the chapter illustrates practical applications of THE ACE control strategies in real-world scenarios. By understanding the intricacies of frequency control, power system operators and engineers can develop more robust and resilient systems, capable of withstanding the dynamic nature of modern power grids.

I.2 Structure of a Power System:

A power system comprises generators, transmission lines, transformers, and distribution networks delivering electricity to consumers. Generators produce electricity from various energy sources, such as fossil fuels, nuclear energy, and renewable resources like wind and solar power. Transmission lines carry this electricity over long distances, while transformers adjust

voltage levels as electricity moves from high-voltage transmission lines to lower-voltage distribution networks. These distribution networks ultimately deliver power to homes, businesses, and industries.

The three-area model simplifies the complexity of power systems by dividing the network into three interconnected areas, each representing a generation-consumption zone. These areas encompass both power generation facilities and the load they serve. By segmenting the system in this manner, it becomes easier to study and understand the interactions and dependencies within the network.

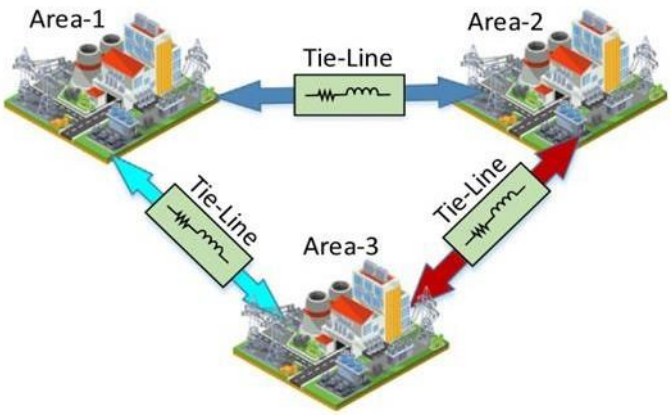


Figure I.1: three-area module [1]

These three areas interact through tie lines, which are the transmission lines that connect them. Tie lines are crucial for maintaining system stability and reliability, as they allow for the transfer of electricity between areas. This interconnection enables the system to balance supply and demand more effectively. For instance, if one area experiences a surplus in generation while another faces a deficit, electricity can be transferred from the surplus area to the deficit area through the tie lines, helping to maintain a steady and balanced system frequency.

The three-area model also facilitates the implementation of control strategies aimed at enhancing system stability. By monitoring and managing the power flows across the tie lines, system operators can better coordinate generation resources, respond to load changes, and mitigate the impact of disturbances. This interconnected approach improves the resilience of

the power system and enhances its efficiency, ensuring that electricity is delivered where and when it is needed most.

In summary, the three-area model serves as an essential tool in understanding and managing the complexities of modern power systems. By breaking down the system into more manageable sections and focusing on the interactions between them, it allows for more effective control and optimization of the electricity supply, contributing to the overall stability and reliability of the power grid.

I.3 Modeling the system :

we examined the dynamic interactions and control mechanisms within each interconnected area to maintain frequency stability and reliable operation. Each area in the three-area model is characterized by key equations that describe frequency deviation, changes in mechanical power, tie line power flow, and governor response. These equations form the foundation of our analysis and provide insights into how imbalances between generation and load are managed to ensure a stable and efficient power system.

I.3.1 frequency deviation differential equation:

By analyzing the frequency deviation equation, we can quantify the extent to which the system's frequency deviates from its nominal value due to changes in load or generation. Moreover, the main equation of frequency deviation is described as followed:

$$\frac{d\Delta f^i}{dt} = \frac{1}{2H^i}(\Delta P_m - \Delta P^i_L - \Delta P^i_{tie}) - \frac{D^i}{2H^i}\Delta f^i \qquad \textbf{(I.2)}$$

We have three areas that describes different frequency deviation to each area so we'll get :

Area 1:

$$\frac{d\Delta f^1}{dt} = \frac{1}{2H^1}(\Delta P^1_m - \Delta P^1_L - \Delta P^1_{tie}) - \frac{D^1}{2H^1}\Delta f^1 \qquad \textbf{(I.2)}$$

Area 2 :

$$\frac{d\Delta f^2}{dt} = \frac{1}{2H^2}(\Delta P^2_m - \Delta P^2_L - \Delta P^2_{tie}) - \frac{D^2}{2H^1}\Delta f^2 \qquad \textbf{(I.3)}$$

Area 3 :

$$\frac{d\Delta f^3}{dt} = \frac{1}{2H^3}(\Delta P^3_m - \Delta P^3_L - \Delta P^3_{tie}) - \frac{3}{2H^1}\Delta f^3 \qquad \textbf{(I.4)}$$

Where:

$\boldsymbol{\Delta f}$: is the deviation from the nominal frequency f_s.

$\boldsymbol{\Delta P_m}$: the total change in mechanical power.

$\boldsymbol{\Delta P_{L}^{i}}$ the electrical power imbalance.

$\boldsymbol{\Delta P_{tie}^{i}}$ the change in total power flow from area i on all its tie lines.

$\boldsymbol{H}$:the inertia of the rotating masses.

$\boldsymbol{D^{i}}$ the load damping coefficient of the area.

I.3.2 Change in total power:

The equation that expresses the change in total power flow is expressed as followed

$$\frac{d\Delta P_{tie}^{i}}{dt} = 2\pi \left(\Delta f^{i} \sum_{\substack{j=1 \\ j\neq i}}^{n} T_{ij} - \sum_{\substack{j=1 \\ j\neq i}}^{n} T_{ij}\Delta f^{j}\right) \qquad \textbf{(I.5)}$$

Area 1 :

$$\frac{d\Delta P_{tie}^{1}}{dt} = 2\pi \left(\Delta f^{1} \sum_{\substack{j=1 \\ j\neq 1}}^{n} T_{1j} - \sum_{\substack{j=1 \\ j\neq 1}}^{n} T_{1j}\Delta f^{j}\right) \qquad \textbf{(I.6)}$$

Area 2:

$$\frac{d\Delta P_{tie}^{2}}{dt} = 2\pi \left(\Delta f^{2} \sum_{\substack{j=1 \\ j\neq 2}}^{n} T_{2j} - \sum_{\substack{j=1 \\ j\neq 2}}^{n} T_{2j}\Delta f^{j}\right) \qquad \textbf{(I.7)}$$

Area 3 :

$$\frac{d\Delta P_{tie}^{3}}{dt} = 2\pi \left(\Delta f^{3} \sum_{\substack{j=1 \\ j\neq 3}}^{n} T_{3j} - \sum_{\substack{j=1 \\ j\neq 3}}^{n} T_{3j}\Delta f^{j}\right) \qquad \textbf{(I.8)}$$

Where:

$\boldsymbol{\Delta f^{i}}$: the local frequency in area i and j

$\boldsymbol{T_{i}}$:the synchronizing torque coefficient between area i and j.

:the number of areas of the system.

I.3.3 Governor:

- The governor differential equations is described as follow :

$$\Delta P_{g}(s) = \frac{1}{1+T_{g}s} \cdot \Delta P_{c}(s) \qquad \textbf{(I.9)}$$

in order to be able to get $\frac{\boldsymbol{d\Delta P^{i}}}{\boldsymbol{dt}}$ we need to find ΔP_{c} so the equation of ΔP_{c} is as follow :

$$\Delta P_{c}^{i} = -\frac{1}{R}\Delta f^{i} + \Delta P_{ref}^{i} \qquad \textbf{(I.10)}$$

Where :

$\boldsymbol{\Delta P}$: is the control signal to the governor.

$\boldsymbol{\Delta P_g}$: the valve position from the governor to the turbine, $\boldsymbol{T_g}$: the time constants of the governor

Replacing the equation of ΔP_c^i in The governor differential equation, so the governor differential equation that describes each area becomes :

Area 1 :

$$\frac{d\Delta P_g^1}{dt} = \frac{1}{RT_{g1}} \cdot \Delta f^1 + \frac{1}{T_{g1}} . \Delta P_{ref}^1 - \frac{1}{T_{g1}} \Delta P_g^1 \qquad \textbf{(I.11)}$$

Area 2 :

$$\frac{d\Delta P_g^2}{dt} = \frac{1}{RT_{g2}} \cdot \Delta f^2 + \frac{1}{T_{g2}} . \Delta P_{ref}^2 - \frac{1}{T_{g2}} \Delta P_g^2 \qquad \textbf{(I.12)}$$

Area 3 :

$$\frac{d\Delta P_g^3}{dt} = \frac{1}{RT_{g3}} \cdot \Delta f^3 + \frac{1}{T_{g3}} . \Delta P_{ref}^3 - \frac{1}{T_{g3}} \Delta P_g^3 \qquad \textbf{(I.13)}$$

I.3.4 The Turbine :

The turbine differential equation is described as follow :

$$\Delta P_m(s) = \frac{1}{1+T_t s} \cdot \Delta P(s) \qquad \textbf{(I.14)}$$

Applying Laplace inverse transformer we get for the three areas :

Area 1 :

$$\frac{d\Delta P_m^1}{dt} = \frac{1}{T_{t3}} \cdot \Delta P_g^1 - \frac{1}{T_{t1}} \Delta P_m^1 \qquad \textbf{(I.15)}$$

Area 2 :

$$\frac{d\Delta P_m^2}{dt} = \frac{1}{T_{t2}} \cdot \Delta P_g^2 - \frac{1}{T_{t2}} \Delta P_m^2 \qquad \textbf{(I.16)}$$

Area 3 :

$$\frac{d\Delta P_m^3}{dt} = \frac{1}{T_{t3}} \cdot \Delta P_g^3 - \frac{1}{T_{t3}} \Delta P_m^3 \qquad \textbf{(I.17)}$$

Also the frequency characteristics (β) for each area are defined as

$$\beta_1 = D_1 + \frac{1}{R_1} = 0.3483 \qquad (\text{I.}\mathbf{18})$$

$$\beta_2 = D_2 + \frac{1}{R_2} = 0.3823 \qquad (\text{I.}\mathbf{19})$$

$$\beta_3 = D_3 + \frac{1}{R_3} = 0.3696 \qquad (\text{I.}\mathbf{20})$$

In our case the areas are connected through tie-lines so the change in mechanical power becomes :

$$\Delta P_{m1} = \frac{-\Delta_\omega}{R_1} \qquad (\text{I. } \mathbf{21})$$

$$\Delta P_{m2} = \frac{-\Delta_\omega}{R_2} \qquad (\text{I. } \mathbf{22})$$

$$\Delta P_{m3} = \frac{-\Delta_\omega}{R_3} \qquad (\text{I. } \mathbf{23})$$

Thus, the steady-state frequency deviation for load change of each area becomes :

$$\Delta_{\omega 1} = \frac{-\Delta PL_1}{\beta_1 + \beta_2 + \beta_3} \qquad (\text{I. } \mathbf{24})$$

$$\Delta_{\omega 2} = \frac{-\Delta PL_2}{\beta_1 + \beta_2 + \beta_3} \qquad (\text{I. } \mathbf{25})$$

$$\Delta_{\omega 2} = \frac{-\Delta PL_3}{\beta_1 + \beta_2 + \beta_3} \qquad (\text{I. } \mathbf{26})$$

And the tie-line power deviation becomes :

$$\Delta P_{12} = \frac{\beta_1 \times (-\Delta PL_1)}{\beta_1 + \beta_2 + \beta_3} \qquad (\text{I. } \mathbf{27})$$

$$\Delta P_{23} = \frac{\beta_2 \times (-\Delta PL_2)}{\beta_1 + \beta_2 + \beta_3} \qquad (\text{I. } \mathbf{28})$$

$$\Delta P_{13} = \frac{\beta_3 \times (-\Delta PL_3)}{\beta_1 + \beta_2 + \beta_3} \qquad (\text{I. } \mathbf{29})$$

Where :

$\boldsymbol{\Delta P}$: the mechanical power output from the turbine.

$\boldsymbol{T}$: the time constants of the turbine

I.4 State-space form:

The state space model is a mathematical form that represent the system dynamics, inputs, outputs, in manners, it is easy to study and implement various control strategies. In our case, we have a dynamical system that consists of 12 states variables, three inputs, three measured disturbances and lastly, six outputs and represented in the following form

$$\begin{aligned} \dot{\boldsymbol{x}}(\boldsymbol{t}) &= \boldsymbol{A}\boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{B}\boldsymbol{u}(\boldsymbol{t}) + \boldsymbol{E}\boldsymbol{d}(\boldsymbol{t}) \\ \boldsymbol{y}(\boldsymbol{t}) &= \boldsymbol{C}\boldsymbol{x}(\boldsymbol{t}) \end{aligned} \qquad (\mathbf{I.30})$$

where:

- (t) is the state vector, including frequency deviations $(\Delta f_1, \Delta f_2, \Delta f_3)$, and tie-line power deviation (ΔP_{tie}).
- (t) is the control input vector (e.g., control signals to the generators u_1, u_2).
- (t) represents disturbances such as load changes.
- (t) is the output vector.
- A, B, and C , E are system matrices.

$$(t) = \begin{matrix} \Delta f^1 \\ \Delta f^2 \\ \Delta f^3 \\ \Delta P_g^1 \\ \Delta P_g^2 \\ \Delta P_g^3 \\ \Delta P_m^1 \\ \Delta P_m^2 \\ \Delta P_m^3 \\ \Delta P_{tie}^1 \\ \Delta P_{tie}^2 \\ \Delta P_{tie}^3 \end{matrix} \quad ; \quad (t) = \begin{matrix} \Delta P_{ref}^1 \\ [\Delta P^2{}_{ref}] \\ \Delta P_{ref}^3 \end{matrix} \quad ; \quad (t) = \begin{matrix} \Delta L^1 \\ [\Delta L^2] \\ \Delta L^3 \end{matrix}$$

$$y = \begin{matrix} \Delta f^1 \\ \Delta f^2 \\ \Delta f^3 \\ \Delta P^1{}_{tie} \\ \Delta P^2{}_{tie} \\ [\Delta P_{tie}^3] \end{matrix}$$

With:

A :

$$\begin{matrix} -\frac{D_1}{2H_1} & 0 & 0 & 0 & 0 & 0 & \frac{1}{2H_1} & 0 & 0 & -\frac{1}{2H_1} & 0 & 0 \\ 0 & -\frac{D_2}{2H_2} & 0 & 0 & 0 & 0 & 0 & \frac{1}{2H_2} & 0 & 0 & -\frac{1}{2H_2} & 0 \\ 0 & 0 & -\frac{D_3}{2H_3} & 0 & 0 & 0 & 0 & 0 & \frac{1}{2H_3} & 0 & 0 & -\frac{1}{2H_3} \\ -\frac{1}{R_1 r_{g1}} & 0 & 0 & \frac{-1}{r_{g1}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\frac{1}{R_2 r_{g2}} & 0 & 0 & \frac{-1}{r_{g1}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -\frac{1}{R_2 r_{g3}} & 0 & 0 & \frac{-1}{r_{g3}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{r_{t1}} & 0 & 0 & -\frac{1}{r_{t1}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{r_{t2}} & 0 & 0 & -\frac{1}{r_{t2}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{r_{t3}} & 0 & 0 & -\frac{1}{r_{t3}} & 0 & 0 & 0 \\ 2(T_{12}^0 + T_{13}^0) & -2\pi T_{12}^0 & -2\pi T_{13}^0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -2\pi T_{12}^0 & +2(T_{12}^0 + T_{23}^0) & -2\pi T_{23}^0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -2\pi T_{13}^0 & -2\pi T_{23}^0 & 2(T_{13}^0 + T_{23}^0) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{matrix}$$

$$[\boldsymbol{B}] = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{1}/r_{g1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{1}/r_{g2} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1}/r_{g3} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

I.5 System model stability :

- poles of the system are calculated and expressed as follow :

$$\begin{aligned} \mathrm{P1} &= -14.0707 + 0.0000 \mathrm{P2} \\ &= -13.0296 + 0.0000i \,\mathrm{P3} \\ &= -12.6204 + 0.0000i \,\mathrm{P4} \\ &= -0.5789 + 4.2558i \ \mathrm{P5} \\ &= -0.5789 - 4.2558i \ \mathrm{P6} \\ &= -1.9536 + 0.0000i \ \mathrm{P7} \\ &= -0.6226 + 3.6016i \ \mathrm{P8} \\ &= -0.6226 - 3.6016i \ \mathrm{P9} \\ &= -1.4372 + 2.4391i \ \mathrm{P10} \\ &= -1.4372 - 2.4391i \,\mathrm{P11} \\ &= -1.8223 + 0.0000i \,\mathrm{P12} \\ &= -0.0000 + 0.0000i \end{aligned}$$

Upon analysis, we observe that the system consists of twelve poles, with eleven poles located in the left half-plane and one pole situated at the origin. This configuration indicates that the system is marginally stable, as it includes a pole on the imaginary axis. Furthermore, by examining the system's dynamic step response, we observed oscillatory behavior before the system settles into its steady-state regime. This oscillation is characteristic of the system's transient response, influenced by the presence of the zero pole and the overall pole placement.

I.6 Area Control Error (ACE):

The integral control is composed of a frequency sensor and an integrator. The frequency sensor measures the frequency error and this error signal is fed into the integrator. The input to

the integrator is called the area control error (ACE). ACEs are used as actuating signals to active changes in the reference power set points and when steady state is reached, ΔP_{12} and Δ_ω will be zero. ACE changes the frequency in each area and forces the steady state frequency error to zero. ACE is the combination of deviation in frequency and tie-line power. When all areas have zero ACEs, the total change in power and frequency deviation will be zero steady state error but frequency bias factor will work($\beta \neq 0$). ACE measures area load change and give us good control[5]

If $\mathrm{ACE} < 0$, we must increase generation

If $\mathrm{ACE} > 0$, we must decrease generation

If $\mathrm{ACE} = 0$, the system is stable and no steady state error

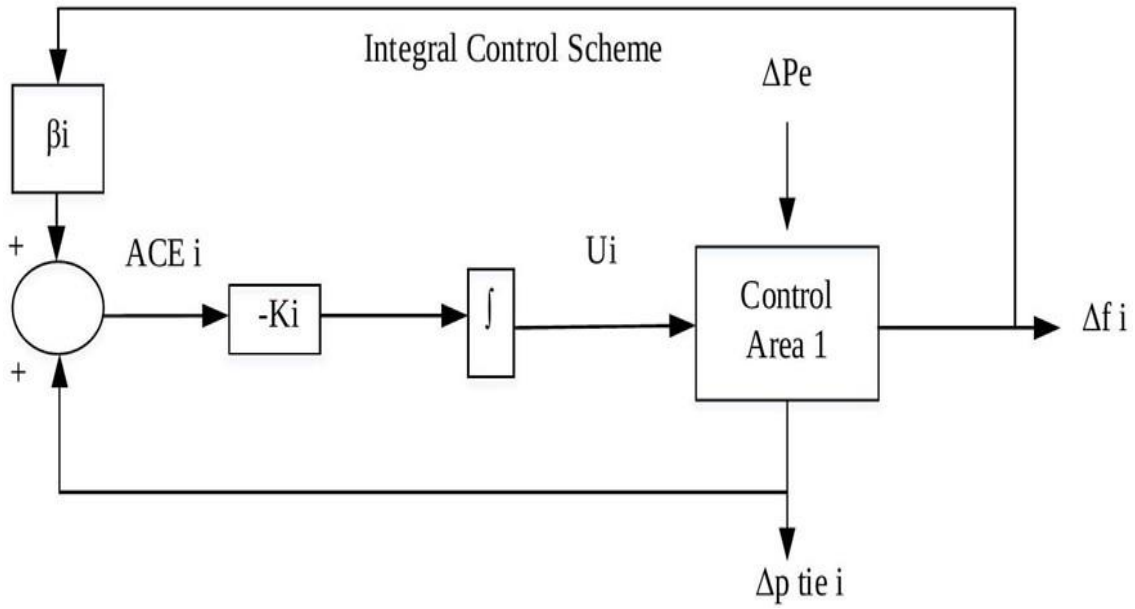


Figure I.3 : Integral Control Scheme

I.6.1 The calculation for ACE are defined as follow :

$$ACE_1 = \Delta P_{12} + \beta_1 \Delta_{\omega 1} \qquad K_1 = \beta_1 \qquad (\mathrm{I}.\mathbf{31})$$

$$ACE_2 = \Delta P_{23} + \beta_2 \Delta_{\omega 2} \qquad K_2 = \beta_2 \qquad (\mathrm{I}.\mathbf{32})$$

$$ACE_3 = \Delta P_{31} + \beta_3 \Delta_{\omega 3} \qquad K_3 = \beta_3 \qquad (\mathrm{I}.\mathbf{33})$$

I.6.2 Simulation for the ACE :

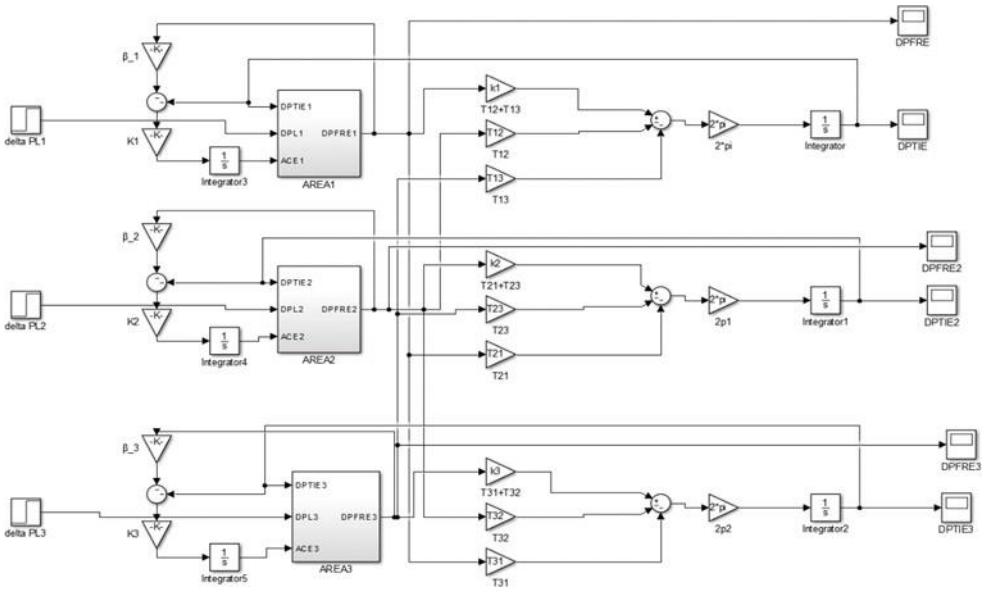


Figure I.4 : The ACE simulation

I.7 System parameters :

- the system characteristic and parameters used for the model plant are as followed

Tableau I.1 : System parameters

Area-1	$T_{t1} = 0.3, T_{g1} = 0.075, T_{r1} = 10, K_{r1} = 0.5, R_{T1} = 2.5,$ $D_1 = 0.08, 2H_1 = 0.16, T_{12} = 0.03$
Area-2	$T_{t2} = 0.33, T_{g2} = 0.08, T_{r2} = 10, R_{T2} = 2.5,$ $D_2 = 0.08, 2H_2 = 0.22, T_{23} = 0.03$
Area-3	$T_{t3} = 0.3, T_{g3} = 0.085, T_{r3} = 10, , R_{T3} = 3,$ $, D_3 = 0.08, 2H_3 = 0.13, T_{13} = 0.03$

Chapter II

Linear model predictive control

II. Chapter II: Linear model predictive control

II.1 Introduction :

Model Predictive Control (MPC) is a method of designing and implementing feedback control systems that, in many situations, perform better than those created by other methods. In addition, MPC provides an effective and general means to design control systems for a large and practically important set of multiple-input, multipleoutput (MIMO) systems.[1]

Recent technological advances have substantially decreased the costs and increased the capability of computers, sensors, and communications, making the benefit/cost ratio for computationally intensive control systems larger and larger. These advances have also greatly increased the need for an effective way to design controllers for complex multiple-input, multiple-output systems by making such systems more and more common. Simultaneously advances in the mathematics and computational algorithms for optimization have greatly improved the speed and reliability of the calculations required by MPC[2]

During the nineties, the theory of MPC has matured substantially. The main reason is probably the use of state-space models instead of input-output models. This has simplified, unified and generalized much of the theory. In the case of non accessible states, the Kalman filter (most easily used in a state-space formulation) simplifies the estimation part, the connections to linear quadratic control give a lot of insight [8], stability theory is almost only possible in a state-space formulation and a lot of recent MPC theory is based on linear matrix inequalities which are most suitable for state-space methods. [3]

In this chapter, we will delve deeply into the foundational concepts of a Model Predictive Control (MPC) algorithm, a sophisticated and widely-used control strategy in modern engineering, specifically within the context of a three-area power system. To start, we will define the scope of admissible systems, outlining the types of systems to which MPC can be effectively applied. This will include a discussion of linear and nonlinear systems, constraints, and the typical operational environments where MPC proves beneficial in multi-area power systems.

Next, we will introduce some fundamental notation and terminology essential for understanding and implementing MPC in a three-area power system. This section will provide clarity on key concepts such as prediction horizon, control horizon, cost functions, and inter-area power exchanges. Detailed examples will be used to illustrate these terms, ensuring that readers can follow along with subsequent sections of the thesis.

Following the foundational groundwork, we will introduce a standard MPC controller, explaining its architecture and operation within a three-area power system. This will include a step-by-step breakdown of how the controller predicts future system behavior, optimizes control actions, and updates control signals based on feedback. We will discuss various optimization algorithms used within MPC, such as quadratic programming and linear programming, and highlight their respective advantages and limitations in the context of power systems.

By the end of this chapter, readers will have a comprehensive understanding of the essential elements of MPC algorithms as applied to three-area power systems, the importance of stability, and the techniques used to achieve it. This foundation will be critical for the more advanced topics and discussions that will follow in the subsequent chapters of this thesis.

II.2 MODEL PREDECTIVE CONTROL ALGORITHM :

The model predictive control or mpc is a control method that consist on mathematical computation of estimated system model in a predetermined finite time horizon, firstly it estimates the discrete system model in future time to determine the optimal control signal for each time instant and for future time instants , there are wide and various methods and techniques for model estimation and we chose the Kalman estimator method in ordre to control our system. So in order to be able to explain how does the MPC algorithm works we break it down to the following steps.

II.3 Model prediction:

The MPC algorithm in general is implemented at digital level, such as devices or controllers , furthermore it would be comprehensible to obtain a discrete time model for the plant , in our case we will use state space form model to obtain the prediction model .

The MPC plant model is defined in discrete time state space as follows:

$$\boldsymbol{x(k+1) = Ax(k) + Bu(k) + B_{MD}u_{MD}(k)} \qquad (\mathbf{II}.\mathbf{1})$$

Where (k) is the state vector,

(k) the input vector,

$u_M(k)$ is called the vector of measured disturbances, i.e. input signals that are not calculated by the controller,

(k) is the output vector.

II.4 Discrete time standard Kalman filter

Firstly, we are going to study the Kalman filter for our linear state space model which is given as:

$$\begin{aligned} \boldsymbol{x_{k+1} = Ax_k + Bu_k,}\ \textbf{with initial states}\ \boldsymbol{x_0}\ \textbf{known} \\ \boldsymbol{y_k = Cx_k + Du_k} \end{aligned} \qquad (\mathbf{II.2})$$

With :$_0$ =0

In ordre to get a stochastic model in nature , we will add process noise ' w_k ' to the model ,in our case the measurement noise ' v_k ' is neglected

$$\begin{aligned} \boldsymbol{x_{k+1} = Ax_k + Bu_k + w_k,}\ \textbf{with initial states}\ \boldsymbol{x_0}\ \textbf{known} \\ \boldsymbol{y_k = Cx_k + Du_k + v_k} \end{aligned} \qquad (\mathbf{II.3})$$

Assuming that the process and the measurement noises are white noises with zero-mean, uncorrelated and have known covariance matrices W and V as,

$$\begin{aligned} \boldsymbol{W = E[w_k w_k^T]} \\ \boldsymbol{V = E[v_k v_k^T]} \end{aligned} \qquad (\mathbf{II.4})$$

We use these covariance matrices to tune the Kalman filter. The algorithmic steps of a discrete-time Kalman filter for a linear process are [50]:

1. Initialize the Kalman filter for time$k = 0$. We can use the initial state of the system (known) for initialization.[50]

$$\begin{aligned} \hat{\boldsymbol{x}}_{\boldsymbol{k}}^{+} = \hat{\boldsymbol{x}}_{\boldsymbol{0}}^{+} = \boldsymbol{E(x_0)} \\ \boldsymbol{P}_{\boldsymbol{k}}^{+} = \boldsymbol{P}_{\boldsymbol{0}}^{+} = \boldsymbol{E}[(\boldsymbol{x_0} - \hat{\boldsymbol{x}}_{\boldsymbol{0}}^{+})(\boldsymbol{x_0} - \hat{\boldsymbol{x}}_{\boldsymbol{0}}^{+})^{\boldsymbol{T}}] \end{aligned} \qquad (\mathbf{II.5})$$

2. Compute the Kalman filter gain (K_f)

$$P^{-}_{k+1} = AP^{+}_{k}A^{T} + W$$
$$k_k = P^{-}_{k+1}C^{T}(CP^{-}_{k+1}C^{T} + V)^{-1} \qquad (\mathbf{II}.\mathbf{6})$$

3. Compute a priori state estimate (predictor).

$$\hat{x}^{-}_{k+1} = A\hat{x}^{+}_{k} + Bu_k \qquad (\mathbf{II}.\mathbf{7})$$

4. Compute output using a priori state estimate

$$\hat{y}^{-}_{k} = C\hat{x}^{-}_{k+1} + Du_k \qquad (\mathbf{II}.\mathbf{8})$$

5. Compute a posteriori state estimate using the current measurement y_k at time k (corrector).

$$\hat{x}^{+}_{k+1} = \hat{x}^{-}_{k+1} + K_{f_k}(y_k - \hat{y}^{-}_{k}) \qquad (\mathbf{II}.\mathbf{9})$$

6. Update the covariance of the state.

$$P^{+}_{k+1} = (I - K_{f_k}C)^{-}{}_{k+1}(I - K_{f_k}C)^{T} + K_{f_k}VK_{f_k}^{T} \qquad (\mathbf{II}.\mathbf{10})$$

7. Set $k := k + 1$ i.e. set $P^{+}_{k} = P^{+}_{k+1}$ and $\hat{x}^{+}_{k} = \hat{x}^{+}_{k+1}$ & repeat step 2 to 6 .

What Kalman filter does is: Every time a measurement is available, it updates the predicted state and covariance of the state estimation error. As the time propagates, the estimated state will finally converge to the true value of the state. So Kalman filter is a recursive estimator.[50]

In the above algorithm, as the iteration continues, the Kalman filter gain kfk will reach a steady state value and will remain constant. This is usually referred to as the steady state Kalman filter gain .[50]

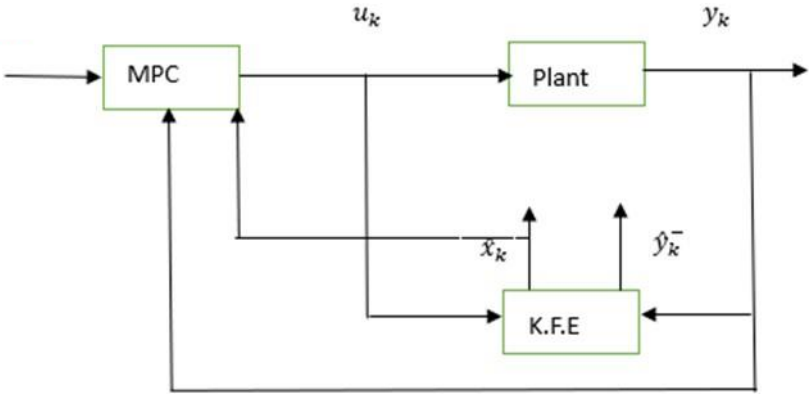


Figure II.1 : output feedback MPC

II.5 Cost function:

In order to reach a desired reference, we need an optimal control signal that could achieve it, for that the construction of a cost function is necessary do; the design of the cost

function depends on what we look for to minimize or maximize. Common form of cost function is the quadratic form.

In our case we want to minimize both the frequency deviation and change in tie line power flow , the quadratic cost function respects both deviation from a state reference and changes in the control signal and is defined in the following equation :

$$\min \; \underbrace{(\boldsymbol{x}_{N_p} - \boldsymbol{x}_{ref,N_p})^T \boldsymbol{S} (\boldsymbol{x}_{N_p} - \boldsymbol{x}_{ref,N_p})}_{\mathbf{I}} + \sum_{i=0}^{N_p-1} \underbrace{[(\boldsymbol{x}_i - \boldsymbol{x}_{ref,i})^T \boldsymbol{Q}_x (\boldsymbol{x}_i - \boldsymbol{x}_{ref,i}) + \Delta \boldsymbol{u}_i^T \boldsymbol{Q}_u \Delta \boldsymbol{u}_i]}_{\mathbf{J}} \qquad (\mathbf{II.11})$$

Where:

$$\Delta u_i = (k+i) - u(k+i-1)$$

$x_{ref} =$ state reference

$x_{N_p} =$ state predicted

$Q_x =$ weight matrices

$Q_u =$ weight matrices

S = weight matrices

A penalty on Δu_i punishes rapid changes in the input signal, which can be used to reduce oscillations. According to a penalty on rapid changes in the input signal, it introduces integral action. However, this is coupled to the prediction horizon. Stationary errors can appear even if integral action is introduced via a penalty on Δu_i if the prediction horizon is not long enough.[48]

In the cost function stated above, the prediction horizon (N_p) and the control horizon (N_u) are not the same as ($N_p = 7$) and($N_u = 2$). The MPC_Toolbox, which we are using for implementation in Simulink, uses the formulation where N_u are distinct from N_p.that justifies the values chosen previously. [48]

Where;

$$\boldsymbol{x_{k+1}} = \boldsymbol{f}(\boldsymbol{x_k}, \boldsymbol{u_k})$$

According to this definition of the cost function stated above , a simple criterion function will be:

$$\boldsymbol{I} = \sum_{k=0}^{\infty} [(\hat{\boldsymbol{y}}_k - \boldsymbol{w}_k)^2 + \boldsymbol{y}\boldsymbol{u}_k^2] \qquad (\mathbf{II.12})$$

Where:

y_k is the predicted output at sampling time k, w_k is the reference trajectory at sampling time k and Now the controller output sequence u_{opt} over the prediction horizon stated above is obtained by minimizing the J at each sampling instant.

II.6 Constraints :

Constraints in control are a set of rules that defines the limitations posed by the user or the model plant itself , in the case of the MPC it effects the control signal generated by the controller , meaning that the control signal itself have limitations . The Simulink model predictive controller uses Quadratic Optimization approach (QP) , The QP is a convex problem, i.e. if a solution is found uniqueness is guaranteed. To get a QP the constraints need to be linear .They are thus on the form:

$$\boldsymbol{x_o = \text{initial state value given above}}$$
$$\boldsymbol{u_{\min} \leq u \leq u_{\max},\ i = 0, \ldots\ldots, N_p - 1} \qquad (\mathbf{II.13})$$

In our case u_{min} and u_{max} are a variable values that varies with different control scenarios.

II.7 Optimization problem and algorithm:

The optimization vector is:

$$\boldsymbol{U = [u^T(k), \ldots, u^T(k + N_p - 1)]^T} \qquad (\mathbf{II.14})$$

In our case a shorter control horizon than prediction horizon is used, so it is assumed that

$$\boldsymbol{(k + i) = u(k + N_u - 1)} \ \textbf{For all } \boldsymbol{i \geq N_u}. \qquad (\mathbf{II.15})$$

After determining the optimization vector, it is now clear that the problem now needs to be rewritten in terms of U only. This is in principle straightforward since [16]:

$$\boldsymbol{x(k) = A^k x(0) + \sum_{j=0}^{k-1} A_{MD}^{k-1-j}(Bu(j) + B_{MD} u_{MD}(j))} \qquad (\mathbf{II.16})$$

Finally the optimization problem becomes:

$$\boldsymbol{U_{\min} \leq U^T H U + h^T U} \qquad (\mathbf{II.17})$$

Where the matrices H and the vector h are build up by x_{ref}, u_{ref}, x_0, Q_x, Q_u, S, A, B and$C$.

The MPC-algorithm can now be summarized as:

a. Measure the current state $x(k)$ or estimate it using the Kalman filter integrated in the MPC controller

b. Solve the k-th optimization problem to obtain

$$\boldsymbol{U = [u^T(k), \dots, u^T(k + N_p - 1)]^T} \qquad (\mathbf{II.18})$$

c. Apply (k) to the system.

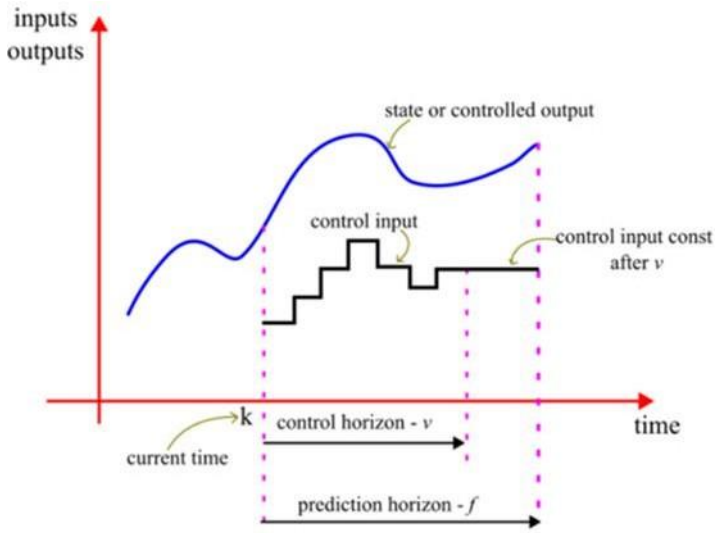
d. Update time $k = k + 1$ and repeat from step 1.

II.8 Integral action and offset in MPC :

When a linear MPC is used to control a nonlinear plant away from the point of linearization: In this case, the MPC is based on the linearized model of the plant. The linear plant model shows correct behavior only at or around the point of linearization. If the plant is operated at regions which lie away from the point of linearization, then the linearly approximated model may not be able to show the true nonlinear behavior of the plant, and hence the plant-model mismatch arises. Under such scenarios, linear MPC (based on the linearized model of the plant) when applied to the nonlinear plant may show finite steady state error or offset.[50]

In an offset free steady-state , the output of the three area power system is equal to the value of the set point reference desired, that it self is an integral action made by the MPC to assure zero offset in the steady state regime[50] .

Sd



IIFigure II.2 : illustration on how MPC deploy its control input

II.9 Digital simulation:

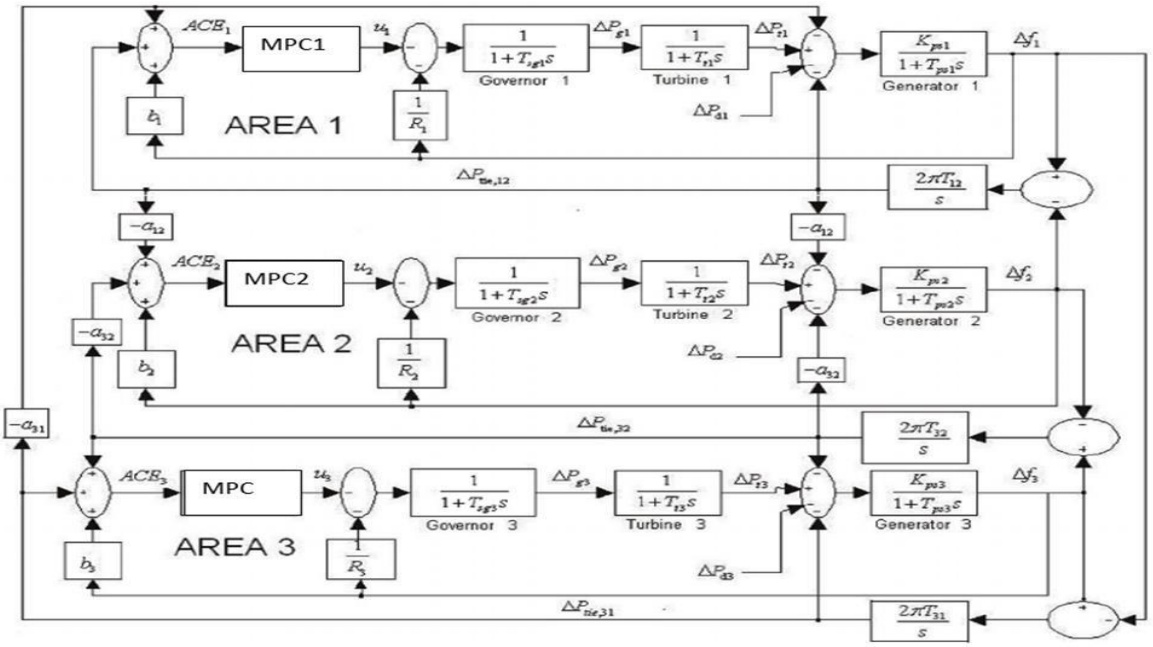


Figure II.3: the proposed MPC block scheme of three areas power system

In other way the mpc controller block is broken into a lot element, we will refer to the essential elements and how they works :

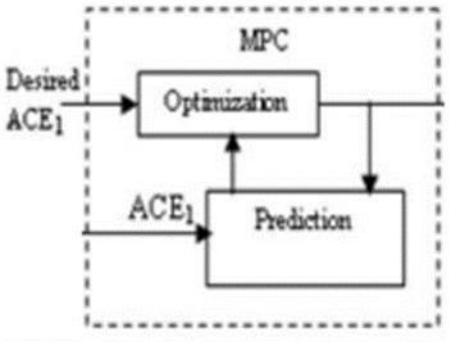


Figure II.4 : the MPC general structure[48]

In the figure above there is the MPC structure, In this control system, the ACE (Area Control Error) signal serves as both the manipulated output (MO) and the input for the Model Predictive Control (MPC) controller. Here is a detailed breakdown of the process:

1. **ACE Signal**: The ACE signal represents the difference between the actual and desired values in the control system. It is a critical parameter that the controller aims to minimize.

2. **Predictor Block**: The MO signal is fed into the predictor block. This block is responsible for generating the discrete state model of the system. Essentially, it predicts the future behavior of the system based on current and past inputs.

3. **Discrete State Model**: Within the predictor block, the system's dynamics are modeled in a discrete-time framework. This model predicts how the system will respond over time, given the current ACE signal and other relevant inputs.

4. **Proposed Control Signal**: The output of the predictor block is a proposed control signal. This signal represents the predicted control action, it is fed to the optimization block ,

5. **Optimization Block**: The proposed control signal is received by the the optimization block. Here, an advanced mathematical technique(Quadratique optimization method) is used to determine the optimal control action at the current instant. This involves solving an optimization problem that minimizes a cost function, typically balancing performance and resource constraints.

6. **Optimal Control**: The optimal control action calculated by the optimization block is then applied to the plant model. This action adjusts the system's inputs to correct the ACE signal, thereby steering the system towards its desired state.

This process ensures that the system continuously adjusts its behavior in response to changing conditions, maintaining optimal performance and stability.

II.10 Importance of LMPC :

II.10.1 Simplicity and Efficiency:

- LMPC uses linear models, which are simpler and computationally more efficient compared to nonlinear approaches. This simplicity translates to faster computation times and easier implementation [9].
- Linear models are often easier to interpret and understand than nonlinear models, making LMPC particularly suitable for applications where transparency and interpretability are important [21].

II.10.2 Proven Reliability:

- LMPC has a well-established theoretical foundation and has been widely used in industrial applications. Its reliability and robustness are well documented, making it a trusted choice for many control applications [8].
- The simplicity and stability of linear models make LMPC less susceptible to numerical errors and modeling inaccuracies, ensuring consistent and reliable performance in practice [22].

II.10.3 Ease of Implementation:

- The linear nature of LMPC makes it easier to implement and tune. It requires fewer computational resources and a less complex software infrastructure, which simplifies deployment and maintenance [9].
- LMPC can often be implemented using standard control software and hardware, making it accessible to a wide range of users and applications. This ease of implementation reduces the barrier to adoption and facilitates rapid deployment [23].

II.11 Impacts of LMPC:

II.11.1 Reliable Frequency Control:

- LMPC provides consistent and reliable frequency control, ensuring that the power system operates within desired frequency limits. This reliability is essential for maintaining the stability and security of the power grid [8].
- The linear nature of LMPC makes it well-suited for frequency regulation tasks, where the dynamics of the system can often be adequately captured by linear models. By adjusting control inputs based on linear predictions, LMPC can effectively stabilize frequency fluctuations and maintain grid stability [24].

II.11.2Operational Simplicity:

- The simplicity of LMPC translates to ease of operation and maintenance. It reduces the need for specialized skills and resources, making it an attractive option for many power system operators [9].

- LMPC's straightforward implementation and tuning process allow control engineers to quickly deploy and fine-tune control strategies, minimizing downtime and maximizing operational efficiency [25].

II.11.3 Efficiency in Standard Conditions:

- LMPC is highly efficient in scenarios where system dynamics can be well-approximated by linear models. In such conditions, it ensures optimal performance without the need for excessive computational overhead, making it an economical choice [8].
- By exploiting the linearity of system dynamics, LMPC can achieve stable and efficient control with minimal computational resources. This efficiency is particularly valuable in large-scale power systems, where computational complexity can become a limiting factor [26].

Chapter III

Neural Network Predective Control

III. Chapter III : Neural Network Predictive Control

III.1 Neural network:

A neural network is a method in artificial intelligence that teaches computers to process data in a way that is inspired by the human brain. It is a type of machine learning process, called deep learning that uses interconnected nodes or neurons in a layered structure that resembles the human brain.

III.2 Predictive control:

Predictive control, specifically model predictive control (MPC), is a control strategy that uses a model of the system to predict future behavior and optimize control actions. MPC solves an optimization problem at each control step, ensuring that future system results meet the desired performance criteria while respecting constraints.

III.3 Neural Network Predictive Control

III.3.1 Architecture:

NNPC integrates a neural network model of system dynamics with an MPC framework. The neural network is trained to predict system behavior, while the MPC algorithm optimizes control actions based on these predictions. Figure 1 illustrates a typical NNPC architecture, in which the neural network serves as the system model within the predictive control loop.

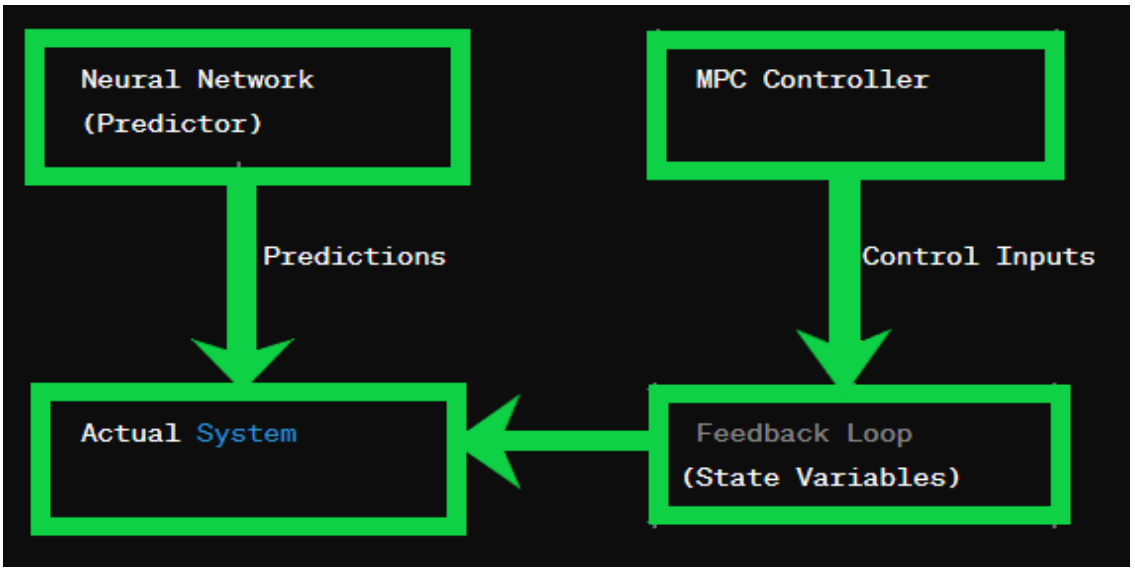


Figure III.1 : NNPC architecture

III.3.2 Training methods :

Neural network training within NNPC involves several techniques. Supervised learning with backpropagation is common, where the network learns from labeled data. Reinforcement learning is another method by which the network learns optimal actions through trial and error, receiving feedback from the environment. Hybrid approaches combine elements of both, thereby improving the efficiency and performance of network learning.

III.3.3 neural network predictive controller :

The neural network predictive controller that is implemented in the Deep Learning Toolbox™ software uses a neural network model of a nonlinear plant to predict future plant performance. The controller then calculates the control input that will optimize plant performance over a specified future time horizon. The first step in model predictive control is to determine the neural network plant model (system identification).

III.3.4 Mathematical Formulation

a System Model :

The system dynamics in NNPC are typically represented as :

$$\mathbf{x_{k+1}} = (\mathbf{x_k} + \mathbf{u_k}) \qquad (\text{III. } \mathbf{1})$$

Where : x_k is the state vector at time step k , and u_k is the control input. The function f is approximated by the neural network.

b Cost Function :

The control objective in NNPC is to minimize a cost function over a prediction horizon N :

$$\boldsymbol{J} = \sum_{\boldsymbol{i=k}}^{\boldsymbol{k+N}} \boldsymbol{L}(\boldsymbol{x_i}, \boldsymbol{u_i}) + \emptyset(\boldsymbol{x_k} + \boldsymbol{N}) \qquad (\text{III. } \mathbf{2})$$

Here, $(x_i + u_i)$ denotes the stage cost at each time step, and $\emptyset(x_k + N)$ represents the terminal cost at the end of the prediction horizon.

Constraints

NNPC incorporates constraints on both state and control variables to ensure feasible and safe operation :

$$\boldsymbol{x_{min}} \leq \boldsymbol{x_k} \leq \boldsymbol{x_{max}} \qquad (\text{III. } \mathbf{3})$$

$$\boldsymbol{u_{min}} \leq \boldsymbol{u_k} \leq \boldsymbol{u_{max}} \qquad (\text{III. } \mathbf{4})$$

III.3.5 Optimization methods

The optimization process in NNPC can be complex due to the nonlinear nature of the system and the high dimensionality of the control problem. Common optimization methods include:

a Gradient-based methods

Gradient-based methods use the gradient of the cost function to iteratively update control actions. Techniques such as gradient descent and its variants, such as stochastic gradient descent (SGD), are frequently used for their computational efficiency and effectiveness.

b Evolutionary algorithms

Evolutionary algorithms, such as genetic algorithms (GA), mimic the process of natural selection to search for optimal solutions. These algorithms evolve a population of candidate solutions over several generations, applying operations such as selection, crossover and mutation.

c Sequential Quadratic Programming (SQP)

Sequential quadratic programming (SQP) is an iterative method used for nonlinear optimization. It solves a sequence of quadratic programming subproblems, each approximating the original nonlinear problem. SQP is well suited to problems with constraints and nonlinear objectives.

d Particle Swarm Optimization (PSO)

The social behavior of birds in flocks or schools of fish inspire particle swarm optimization (PSO). It optimizes a problem by iteratively improving a population of candidate solutions (particles), guided by their own best-known positions and the best-known positions of the swarm.

III.3.6 Case Studies and Applications

NNPC has been successfully applied in various fields, including automotive control systems, robotic motion planning, and industrial process control. Each case study demonstrates

how NNPC can handle complex, dynamic systems with multiple constraints, providing superior performance and adaptability compared to traditional control methods.

III.4 System Identification :

The first stage of model predictive control is to train a neural network to represent the forward dynamics of the plant. The prediction error between the plant output and the neural network output is used as the neural network-training signal. The process is represented by the following figure:

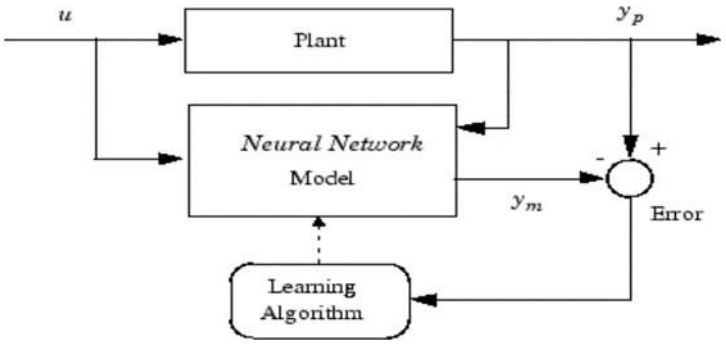


Figure III.2: the neural network training

The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output. The structure of the neural network plant model is given in the following figure:

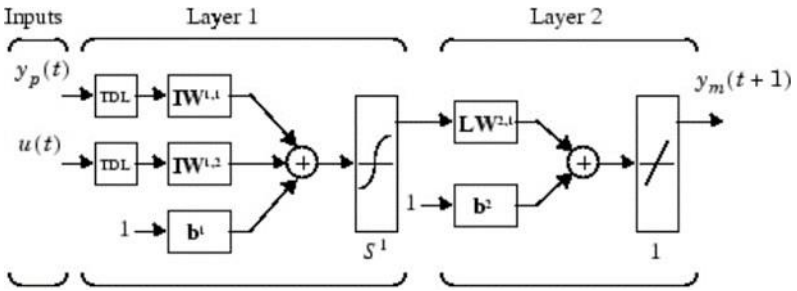


Figure III.3: The structure of the neural network plant model

III.5 Control Problem Formulation:

In MPC algorithms at each consecutive sampling instant k a set of Future control increments is calculated

$$\Delta u(k) = \begin{bmatrix} \Delta u(k/k) \\ \Delta u(k + N_u - 1/k) \end{bmatrix} \qquad (III.5)$$

The objective is to minimise differences between the reference trajectoryThe minimised costFunction is usually:

$$J(k) = \sum_{p=1}^{N} (y^{ref}(k + p/k) - \hat{y}(k + p/k))^2 + \sum_{p=0}^{N_u} \lambda_P (\Delta u(k + p/k))^2 \qquad (III.6)$$

Where $\lambda_P > 0$ are weighting coefficients. Only the first element of the determined

It is assumed that

- u(k + p|k) = 0 for p ≥ Nu, And Nu is the control horizon.
- Yref(k + p|k) and predicted output values ˆy(k + p|k) over the prediction horizon N ≥ Nu and to penalise excessive control increments.

At the Next sampling instant, k + 1, the prediction is shifted one step forward and the Whole procedure is repeated. ***Figure III.4*** illustrates the general idea of MPC as follow :

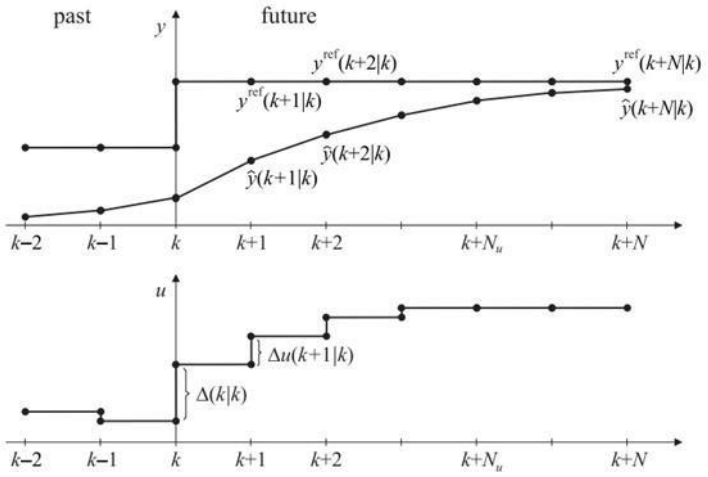


Figure III.5: The principle of predictive control

III.6 NNPC Simulink Block:

The neural network Simulink block consist of two inputs and one output

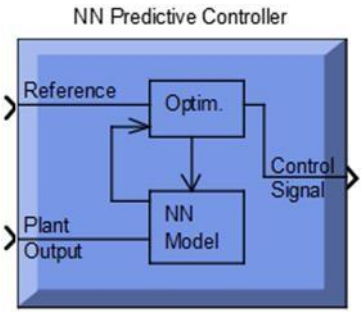


Figure III.6 : NNPC Simulink block

☑ **Inputs :**

Reference: it is the tracking set point that we want the output signal of the trained system to follow.

Plant output: is the output of the plant that the NNPC is being applied to .

☑ **Outputs :**

The control signal : is the control signal of the neural network predictive controller that is beign applied to the system .

III.6.1 Identification block :

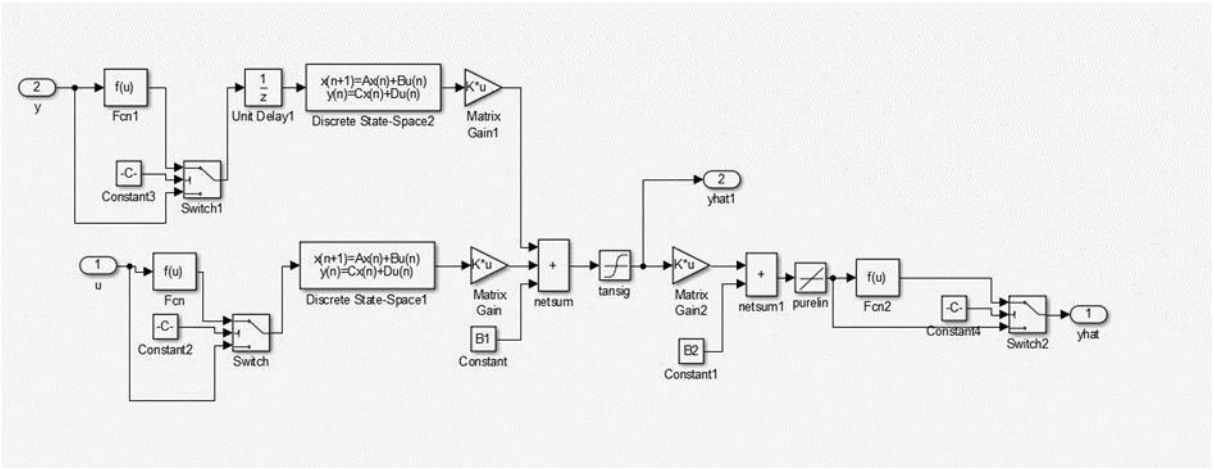


Figure III.7 : NNPC Simulink block

The identification block uses the input and the output of the traind model plant to construct .an estimated plant , in addition to genereating bias and weights to use it in order to have an estimated output that is after injected in s-function block that consist of solving the optimization problem based on the input output constraints declared in the plant identification window

III.7 Simulatin model :

We implemented a neural network predictive control on a three area power system , the system parameters are stated in chapter one in the iluustration below is the Simulink model of the control strategy , the control signal fed to the system , the output (ACE signal) is fed to the controller output to be optimized based on the stated constraints.

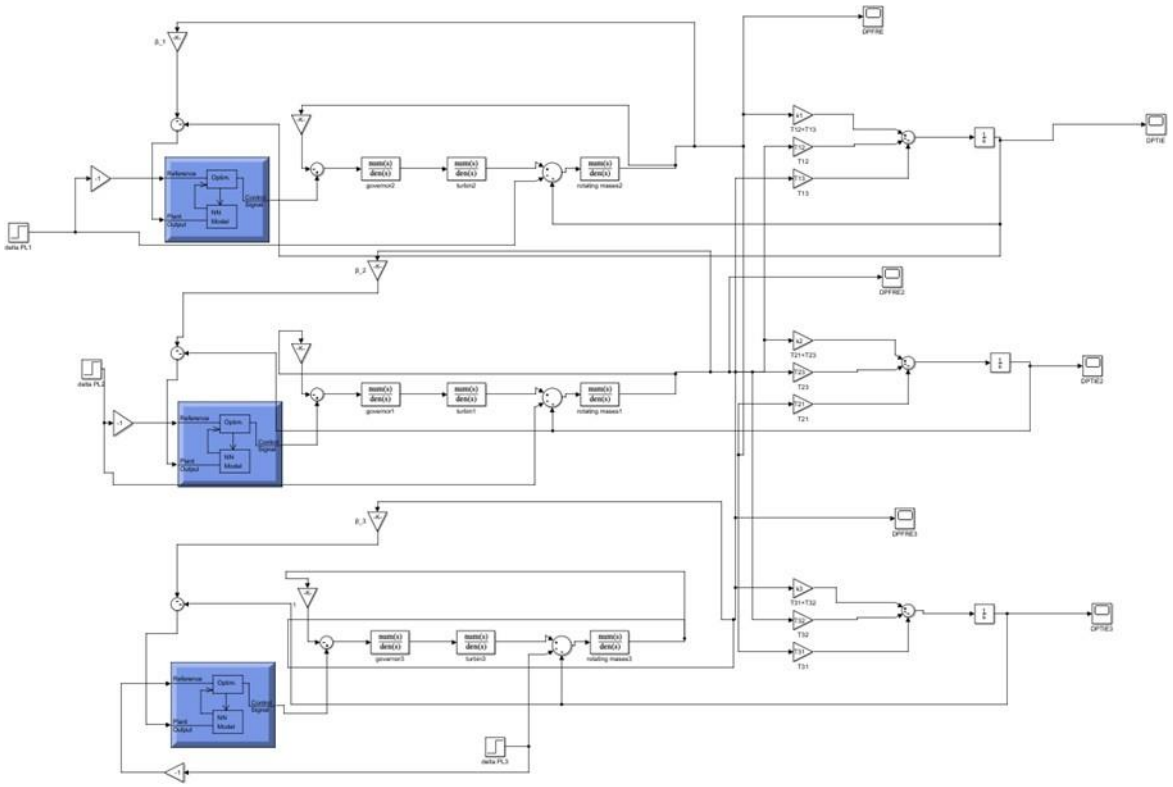


Figure III.8 : NNPC of three area power system

III.8 Importance of NNPC control strategy :

III.8.1 Learning Capability:

- Neural networks excel at learning complex nonlinear relationships within the system, which is particularly beneficial for power systems with nonlinear dynamics. This capability allows NNPC to model and predict system behavior more accurately than linear models [12].

- Neural networks can capture intricate patterns and correlations in data that may be difficult to model using traditional techniques. This learning capability enables NNPC to adapt to a wide range of operating conditions and system configurations [15].

III.8.2 High Accuracy:

- The ability to model nonlinearities and adapt through training results in highly accurate predictions of system behavior. This accuracy translates to more effective control actions and better frequency regulation [13].

- Neural networks can approximate complex nonlinear functions with high precision, allowing NNPC to provide accurate predictions of future system states and outputs. This accuracy is crucial for ensuring stable and reliable operation of power systems [16].

III.8.3Scalability:

- Neural networks can be scaled to handle large datasets and complex system models. This scalability makes NNPC suitable for large power systems with numerous variables and intricate interactions [14].

- By training on diverse datasets that capture the full range of system behaviors, neural networks can generalize well to unseen scenarios, making NNPC applicable to a wide range of power system applications [17].

III.9 Impacts:

III.9.1 Enhanced Predictive Accuracy:

- The superior modeling capability of neural networks leads to more frequency that is accurate predictions. This improved accuracy allows for more precise control actions, which enhances the system's ability to maintain stable frequencies [13].

- Neural networks can capture subtle relationships between input variables and system outputs, leading to more accurate predictions of future system behavior. This enhanced

predictive accuracy enables NNPC to anticipate changes in frequency and respond proactively to ensure system stability [18].

III.9.2 Robust Performance:

- NNPC's ability to handle nonlinearities and uncertainties ensures robust performance across various operating conditions. This robustness is crucial for maintaining stability in a power system subjected to diverse and unpredictable influences [12].

- By incorporating historical data and learning from past experiences, neural networks can adapt to changing system dynamics and disturbances. This adaptability enhances the robustness of NNPC and ensures reliable performance under varying operating conditions [19].

III.9.3 Adaptation to New Patterns:

- Neural networks can be retrained with new data, allowing NNPC to adapt to evolving system behaviors. This continuous learning process ensures that the control strategy remains effective even as system characteristics change over time [14].

- The ability of neural networks to adapt to new patterns and trends in the data makes NNPC well-suited for dynamic and evolving power systems. As system conditions change, NNPC can update its predictive model accordingly, ensuring accurate and reliable control [20].

Chapter IV
Adaptive model predictive control

IV. Chapter IV: Application of AMPC

IV.1 Introduction:

Model Predictive Control (MPC) has emerged as a premier control strategy in modern power systems due to its capacity to manage multivariable control issues with constraints [1]. MPC excels through its predictive capabilities, optimizing control inputs over a future horizon. By anticipating future disturbances and system changes, MPC can make more informed decisions, thus improving the stability and performance of power systems [2]. This approach is particularly advantageous in complex systems where traditional control methods fall short due to their inability to handle multiple input-output relationships and constraints effectively [9].

Adaptive Model Predictive Control (AMPC) advances MPC by incorporating real-time adjustments to the system model, allowing it to adapt to changes in system dynamics [5]. This adaptability is crucial in power systems, which are subject to frequent disturbances and parameter variations such as load changes, generation fluctuations, and faults [3]. AMPC employs online parameter estimation techniques to update the model continuously, ensuring that the controller remains effective under varying conditions [6]. This real-time adaptability enhances the robustness and reliability of the control strategy, making it well-suited for applications in dynamic and uncertain environments [8].

In this chapter, we explore the application of AMPC in a two-area power system, which is representative of interconnected power grids. Each area in such a system has its own generation and load, but they are interconnected via tie-lines. The primary objectives in managing a two-area power system include maintaining system stability, regulating frequency, and managing power flows across tie-lines [4]. Effective control of these factors is essential to ensure the reliable operation of the power system and to prevent cascading failures that can lead to widespread outages [3].

The chapter will detail the process from system modeling to implementation and performance evaluation. We will begin by modeling the two-area power system using state-space representations. This modeling approach provides a structured way to describe the relationships between system states, inputs, and outputs [7]. Accurate modeling is essential for designing an effective MPC strategy, as it allows for precise predictions of future system behavior [1].

Next, we will discuss the implementation of AMPC, including the design of the control algorithm and the online parameter estimation techniques used to adapt the model in real-time.

We will employ Recursive Least Squares (RLS) with an exponential forgetting factor for online parameter estimation, a method known for its efficiency and accuracy in tracking parameter changes [6].

By detailing each step of the process and providing comprehensive explanations and mathematical formulations, this chapter aims to offer a thorough understanding of AMPC and its application in two-area power systems. This knowledge will be valuable for researchers and practitioners looking to enhance the performance and reliability of modern power systems.

IV.2 System modeling:

The system dynamics can be described using state-space models, which capture the relationships between various states (e.g., frequency deviations, power flows) and inputs.

Taking the equations, we are going to use in this chapter so we can have a state space form for the two-area power system written as follow:

$$\Delta \dot{f}_1 = \frac{1}{2H_1}(\Delta P_{m1} - \Delta P_{L1} - D_1 \Delta f_1 - \Delta P_{tie}) \qquad (IV.1)$$

$$\Delta \dot{f}_2 = \frac{1}{2H_2}(\Delta P_{m2} - \Delta P_{L2} - D_2 \Delta f_2 + \Delta P_{tie}) \qquad (IV.2)$$

$$\Delta \dot{P}_{tie} = 2\pi T_{12}(\Delta f_1 - \Delta f_2) \qquad (IV.3)$$

Where:

- Δf_1 and Δf_2 are the frequency deviations in areas 1 and 2.
- ΔP_{m1} and ΔP_{m2} are the mechanical power changes in areas 1 and 2.
- ΔP_{L1} and ΔP_{L2} are the load changes in areas 1 and 2.
- D_1 and D_2 are the damping coefficients.
- H_1 and H_2 are the inertia constants.
- T_{12} is the synchronizing coefficient of the tie-line.

Having those equations will lead us to determine the state space form of the two area power system and it is written in following form:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + Ed(t) \\ (t) &= Cx(t) \end{aligned} \qquad (IV.4)$$

With:

$$A=\begin{bmatrix} -\frac{D_1}{2H1} & 0 & \frac{1}{2H1} & 0 & -\frac{1}{2H1} & 0 & 0 \\ 0 & \frac{D_1}{2H1} & 0 & \frac{1}{2H1} & 0 & -\frac{1}{2H2} & \frac{1}{2H2} \\ -\frac{1}{R_{p-1}} & 0 & -1/r_{g1} & 0 & 0 & 0 & 0 \\ 0 & -1/R_2 r_{g2} & 0 & -1/r_{g2} & 0 & 0 & 0 \\ 0 & 0 & 1/r_{t1} & 0 & -1/r_{t1} & 0 & 0 \\ 0 & 0 & 0 & 1/r_{t2} & 0 & -1/r_{t2} & 0 \\ 2\pi T^0_{12} & -2\pi T^0_{12} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$B=\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1/r_{sg1} & 0 \\ 0 & 1/r_{sg2} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

IV.3 The model predictive control design :

MPC optimizes control inputs by predicting future behavior of the system over a finite horizon and solving an optimization problem at each time step, by using the same algorithm applied in Chapter 2, it is facile to design an MPC for the two-area power system stated above.

As the only difference is in cost function and constraints .The Model Predictive Control algorithm computes optimal control inputs by solving a constrained optimization problem over a finite prediction horizon. In the case of AMPC, the predictive model is continuously updated based on the latest parameter estimates obtained from the online parameter estimation algorithm [9].

The optimization problem typically involves minimizing a cost function that balances control performance by maintaining frequency stability with constraints on system inputs.

IV.3.1 Cost Function :

The objective function or cost function for the MPC typically minimizes a combination of tracking error and control effort:

$$\boldsymbol{J=\sum_{k=0}^{N-1}\left[\|x(k+1\mid k)-x_{ref}(k+1)\|_Q^2+\|(k\mid k)\|_R^2\right]} \qquad (\text{IV.}\mathbf{5})$$

where:

- N is the prediction horizon.
- $x_{re}(k)$ is the reference state vector.

- Q and R are weighting matrices that balance the importance of tracking performance and control effort.

The quadratic term $\|(k+1 \mid k) - x_{ref} \ \ (k+1)\|_Q^2$ ensures the predicted state tracks the reference, while $\| u(k \mid k) \|_R^2$ penalizes large control efforts.

IV.3.2 Constraints:

MPC handles various constraints on states, inputs, and outputs to ensure safe and efficient operation of the power system:

$$\boldsymbol{x_{\min} \leq (k) \leq x_{\max}} \qquad \text{(IV. } \mathbf{6}\text{)}$$
$$\boldsymbol{u_{\min} \leq (k) \leq u_{\max}} \qquad \text{(IV. } \mathbf{7}\text{)}$$
$$\boldsymbol{y_{\min} \leq (k) \leq y_{\max}} \qquad \text{(IV. } \mathbf{8}\text{)}$$

These constraints ensure that the system operates within safe limits, avoiding excessive frequency deviations or power flows. For example:

- State constraints might limit frequency deviations to prevent instability.
- Input constraints could limit the rate of change of generator outputs.
- Output constraints might ensure tie-line power flows do not exceed physical limits.

IV.4 Adaptive mechanism:

Adaptive Model Predictive Control (AMPC) operates by dynamically adjusting its predictive model based on accurate and current estimates of system parameters in real-time [1]. In the case of a two-area power system, crucial parameters such as inertia constants, damping coefficients, and tie-line synchronizing coefficients play pivotal roles in determining system behavior [3]. These parameters directly influence the dynamics of the power system, affecting its stability, frequency regulation, and power flow management across tie-lines.

To ensure that the AMPC controller remains effective in adapting to changing system conditions, it relies on online parameter estimation techniques [5]. One such method, Recursive Least Squares (RLS) with an exponential forgetting factor, is commonly employed for this purpose [7]. The RLS algorithm continually updates parameter estimates based on observed system behavior, effectively capturing variations in system dynamics over time [9]. By incorporating recent measurements and systematically adjusting parameter estimates, RLS enables the AMPC controller to adapt to evolving conditions and maintain optimal performance.

In essence, AMPC leverages online parameter estimation techniques like RLS to iteratively refine its predictive model, ensuring that it accurately reflects the current state of the power

system [6]. This capability enables the controller to make informed decisions and effectively regulate system behavior in real-time, thereby enhancing stability and performance.

IV.5 Online parameter estimation :

Adaptive Model Predictive Control (AMPC) relies on accurate and up-to-date system parameter estimates to adjust its predictive model in real-time. In the context of a two-area power system, these parameters include inertia constants, damping coefficients, and tie-line synchronizing coefficients, among others. Online parameter estimation techniques, such as Recursive Least Squares (RLS) with an exponential forgetting factor, are employed to continuously update these parameters based on observed system behavior [6].

$$(t) = A_0 + \Delta A(t)$$
$$(t) = B_0 + \Delta(t) \qquad \text{(IV. 9)}$$

The estimation process adjusts $\Delta(t)$ and $\Delta B(t)$ to reflect changes in the system

IV.6 Recursive Least Squares (RLS) :

Recursive Least Squares (RLS) is a widely used algorithm for online parameter estimation due to its simplicity and efficiency. It iteratively updates parameter estimates as new data becomes available, adapting to changes in system dynamics over time. The algorithm minimizes the error between predicted and measured system outputs, adjusting the parameter estimates to improve model accuracy [7] .

IV.6.1 The RLS algorithm updates the parameter estimates using the following equations:

$$(\boldsymbol{t}) = [\boldsymbol{A}(\boldsymbol{t}) \quad \boldsymbol{B}(\boldsymbol{t}) \quad \boldsymbol{E}(\boldsymbol{t})]^T \qquad \text{(IV. 10)}$$
$$(\boldsymbol{t}) = \frac{\boldsymbol{P}(\boldsymbol{t})\boldsymbol{\phi}(\boldsymbol{t})}{\boldsymbol{\lambda} + \boldsymbol{\phi}(\boldsymbol{t})^T\boldsymbol{P}(\boldsymbol{t})\boldsymbol{\phi}(\boldsymbol{t})} \qquad \text{(IV. 11)}$$
$$(\boldsymbol{t}+\boldsymbol{1}) = \frac{\boldsymbol{1}}{\boldsymbol{\lambda}}\left[\boldsymbol{P}(\boldsymbol{t}) - \frac{\boldsymbol{P}(\boldsymbol{t})\boldsymbol{\phi}(\boldsymbol{t})\boldsymbol{\phi}(\boldsymbol{t})^T\boldsymbol{P}(\boldsymbol{t})}{\boldsymbol{\lambda} + \boldsymbol{\phi}(\boldsymbol{t})^T\boldsymbol{P}(\boldsymbol{t})\boldsymbol{\phi}(\boldsymbol{t})}\right] \qquad \text{(IV. 12)}$$
$$(\boldsymbol{t}+\boldsymbol{1}) = \boldsymbol{\theta}(\boldsymbol{t}) + \boldsymbol{K}(\boldsymbol{t})[\boldsymbol{y}(\boldsymbol{t}) - \boldsymbol{\phi}(\boldsymbol{t})^T\boldsymbol{\theta}(\boldsymbol{t})] \qquad \text{(IV. 13)}$$

Where:

- **ParameterVector($\boldsymbol{\theta}(\boldsymbol{t})$):**

  The parameter vector (t) encapsulates critical system parameters such as inertia constants (H), damping coefficients (D), and tie-line synchronizing coefficients (T). These parameters influence the dynamic behavior of each area in the power system. For

instance, the inertia constant affects the system's response to frequency changes, while the damping coefficient influences the rate of damping oscillations. Accurate estimation of these parameters is vital for the predictive model to reflect the true dynamics of the system [6].

- **Kalman Gain** $(\boldsymbol{K}(\boldsymbol{t})$

The Kalman gain (t) is a crucial component that determines how much weight should be given to new measurements when updating parameter estimates. A higher Kalman gain places more emphasis on recent measurements, making the parameter updates more responsive to changes in the system. Conversely, a lower Kalman gain relies more on historical data, making the updates more stable but less responsive. The choice of the Kalman gain is influenced by the forgetting factor λ, which we will discuss shortly [6] .

- **Covariance Matrix** $(\boldsymbol{P}(\boldsymbol{t}))$

The covariance matrix (t) represents the uncertainty or variance associated with the parameter estimates. Initially, this matrix might be set to a large value indicating high uncertainty. As more data is collected and the parameter estimates are refined, the values in the covariance matrix decrease, reflecting increased confidence in the estimates. The covariance matrix is updated at each step to reflect the latest state of knowledge about the system parameters [7] .

- **Regressor Vector** $(\boldsymbol{\phi}(\boldsymbol{t}))$

The regressor vector (t) includes the current and past values of input and output variables that influence the parameter estimation process. For a two-area power system, this might include power generation, load demand, and tie-line power flows. The choice of variables in the regressor vector is crucial for capturing the relevant dynamics of the system and ensuring accurate parameter estimation [7] .

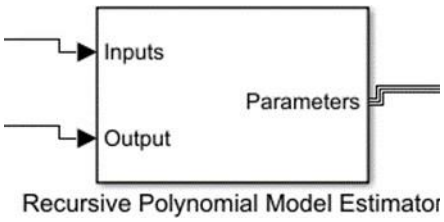


Figure IV.2 : RLS MODEL BLOCK

The recursive polynomial model estimator simulink block , consist of fulfilling the RLS estimation method that identifies the system parameters.

We used two methods estimating the model one is the Kalman filter estimation method the other is gradient estimation method , the efficiency of the estimated varies upon each estimation method we will explain the both methods as follow :

IV.6.2 Kalman Filter Method :

a Introduction:

The Kalman filter is an optimal estimator used to infer the state of a dynamic system from a series of noisy measurements. It combines predictions from a mathematical model of the system with new measurements to produce estimates that are more accurate.

b System Model:

A typical system model for the Kalman filter consists of two equations:

- State Equation (Process Model):

$$\mathbf{x}_{k+1} = \mathbf{A}_k\mathbf{x}_k + \mathbf{B}_k\mathbf{u}_k + \mathbf{w}_k$$

Where $\mathbf{x}_k$ is the state vector at time k, $\mathbf{A}_k$ is the state transition matrix, $\mathbf{B}_k$ is the control input matrix, $\mathbf{u}_k$ is the control input, and $\mathbf{w}_k$ is the process noise (assumed to be Gaussian with zero mean and covariance $\mathbf{Q}_k$).

- Measurement Equation:

$$\mathbf{z}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k$$

The Kalman filter used to estimate plant in chapter one is the same used in the RLS estimation method

c Key Characteristics:

- **Optimality:** The Kalman filter provides the best linear unbiased estimate if the system model is accurate and the noise is Gaussian.
- **Real-Time Capability:** It processes data sequentially, making it suitable for real-time applications.
- **Adaptability:** Can be extended to nonlinear systems using the Extended Kalman Filter (EKF) or Unscented Kalman Filter (UKF).

IV.6.3 Gradient Method :

a Introduction:

The gradient method (or gradient descent) is an iterative optimization algorithm used to minimize a function. It is commonly used in machine learning and system identification to find the optimal parameters of a model.

b Objective Function:

The objective function (θ) represents the cost or error, which we aim to minimize. For polynomial model estimation, this might be the mean squared error between the model output and the actual output.

c Gradient Descent Algorithm:

Gradient descent updates the parameters θ iteratively using the gradient of the objective function.

- Initialization: Choose an initial guess θ_0 for the parameters.
- Iteration: Update the parameters using the rule:

$$\boldsymbol{\theta_{k+1} = \theta_k - \eta \nabla(\theta_k)} \qquad (\text{IV.}\mathbf{14})$$

Where η is the learning rate and $\nabla(\theta_k)$ is the gradient of $J(\theta)$ with respect to θ at iteration k.

d Gradient Computation:

For a polynomial model $y = \phi^{\top}\theta$, where ϕ is the regressor vector, the gradient of the mean squared error (θ) can be computed as:

$$\boldsymbol{\nabla J(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \phi_i^{\top}\theta)(-\phi_i)} \qquad (\text{IV.}\mathbf{15})$$

Where y_i is the actual output and ϕ_i is the regressor vector at sample i.

e Learning Rate:

The learning rate η controls the size of the steps taken towards the minimum. Choosing the right learning rate is crucial:

- Too Small: Convergence will be slow.
- Too Large: May overshoot the minimum or cause divergence.

f Variants of Gradient Descent:

- **Batch Gradient Descent:** Uses the entire dataset to compute the gradient at each iteration.
- **Stochastic Gradient Descent (SGD):** Uses one sample at a time, which can introduce noise but is faster and can escape local minima.
- **Mini-Batch Gradient Descent:** Uses a small subset of the data, balancing the efficiency of SGD and the stability of batch gradient descent.

g Convergence:

Proper convergence depends on the learning rate and the nature of the objective function. Techniques such as adaptive learning rates (e.g., Adam, RMSprop) can help in achieving better convergence.

Both the Kalman filter and gradient methods are powerful techniques for online model estimation. The Kalman filter is optimal for linear systems with Gaussian noise and is highly effective for state estimation and noise reduction. The gradient method, on the other hand, is widely used for optimizing model parameters and is flexible in handling different types of cost functions and models. Proper understanding and implementation of these methods can significantly improve the accuracy and performance of online estimation in dynamic systems.

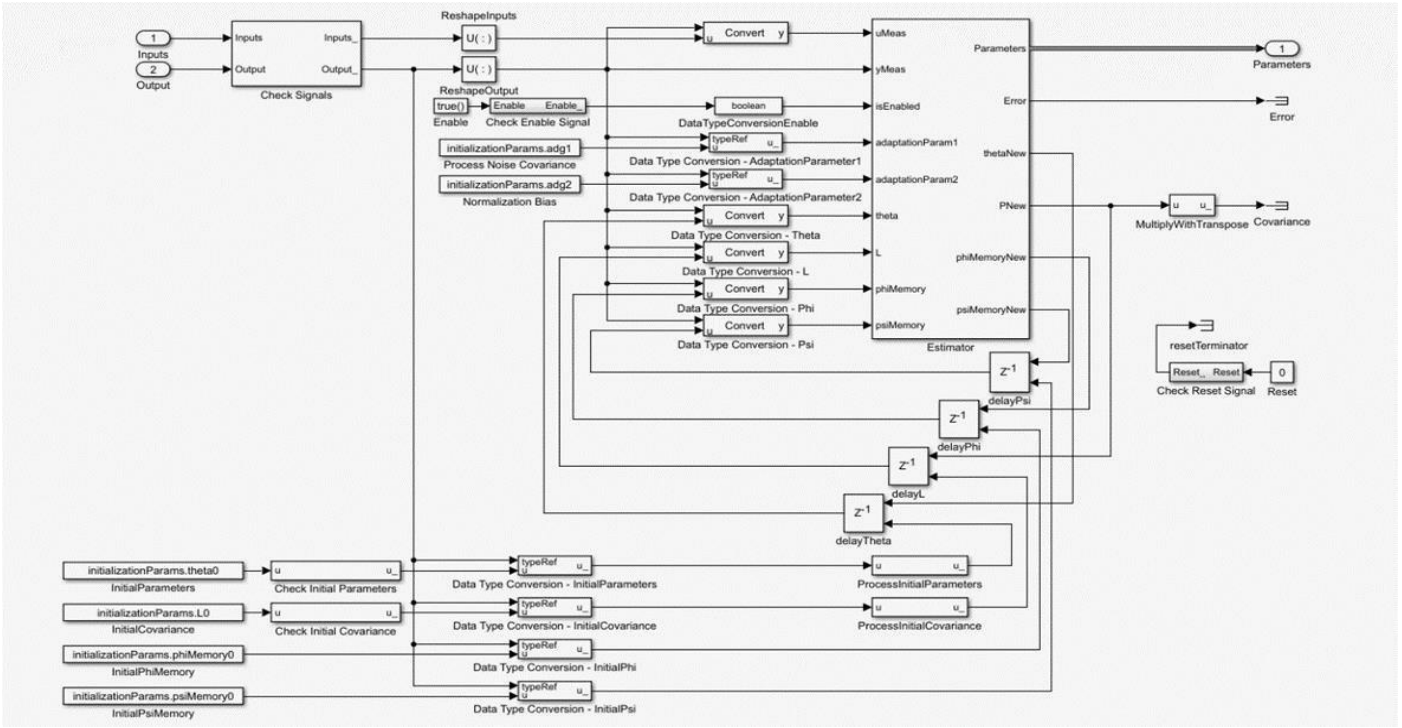


Figure IV.3 : RLS parameters estimation block

After the parameters estimation the AMPC block only accept state space models , so we need a form converter .

Model type converter :

The model type converter , convert the estimated parameters in the estimated ARX model to a state space model ,

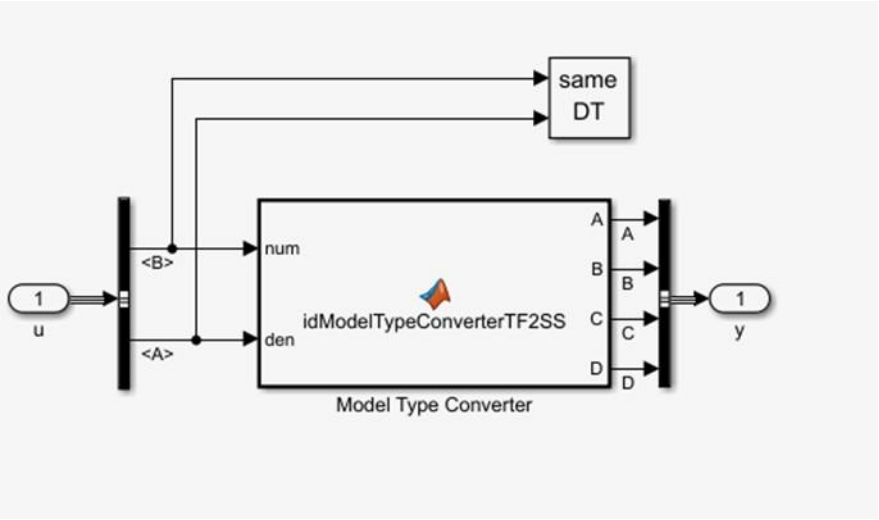


Figure IV.4 :model type converter

After converting to stat space model we now have a fulfilled a fully online identification to the system Model.

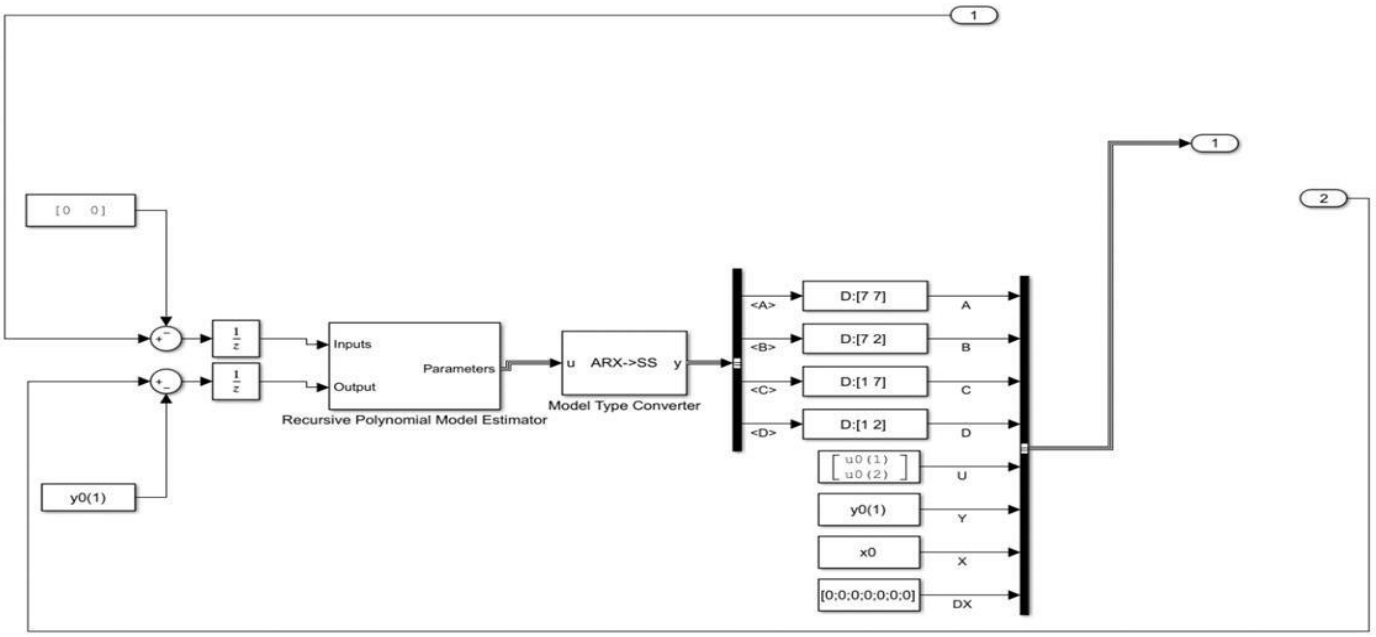


Figure IV.4 :online model estimation in Simulink

So far, we summarized The AMPC algorithm consists of the following steps:

1. Measure the current state (t) and disturbance$d(t)$.
2. Estimate the updated system parameters using the RLS method.
3. Predict future states using the updated model.
4. Optimize the control inputs by solving the MPC optimization problem.
5. Apply the first control input from the optimal sequence.
6. Repeat at the next time step.

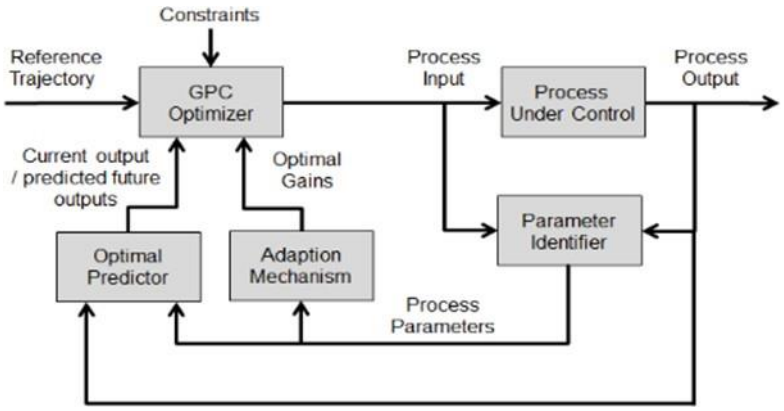


Figure IV.6 : AMPC control of a process[27]

IV.7 Importance of AMPC :

Adaptive Model Predictive Control (AMPC) offers several advantages in the domain of Load Frequency Control (LFC) for two-area power systems. The primary benefits of AMPC include robustness, optimal performance, real-time adaptation, and improved stability. These benefits stem from its ability to dynamically adjust control strategies based on real-time system data and continuously update its model to reflect current operating conditions. Below, we expand on these benefits in detail, citing relevant references.

IV.8 Robustness:

The adaptive nature of AMPC provides significant robustness against parameter variations and system disturbances. This robustness is essential in power systems where load demands and generation capacities can fluctuate frequently.

1. Handling Parameter Variations: AMPC can adapt to changes in system parameters, ensuring that the control strategy remains effective even when the system undergoes significant changes that is beign caused by external elements such as disturbances or unobservable states.

This capability is particularly important in power systems, where environmental conditions, aging infrastructure, and varying load patterns can affect system dynamics .

2. Disturbance Rejection: AMPC's ability to handle and stabilize the disturbance effects on the plant model and enhances the system's ability to maintain stability. By updating continuously the control model based on real-time data, AMPC can effectively diminish the impact of disturbances on system performance .

IV.9 Optimal Performance:

AMPC continuously tunes its control parameters to achieve optimal system performance. This tuning is based on predictive models that consider future behavior and optimize control actions accordingly.

1. Minimizing Cost Functions: AMPC solves an optimization problem at each control step, minimizing the predefined cost function, which includes typically the terms for control effort and deviation from desired performance. This approach ensures that the system operates efficiently, minimizing energy losses and wear on equipment.

2. Performance Metrics: By using advanced prediction models to control the model plant, AMPC can maintain key performance metrics such as frequency regulation and tie-line power flow within desired limits.eaning the ability to handle constraints effectively, This precision is crucial for maintaining the reliability and stability of the power system.

IV.10 Real-Time Adaptation:

The real-time adaptation capability of AMPC allows it to respond swiftly to changes in system conditions, ensuring that the control strategy remains aligned with the current state of the system.

1. Continuous Parameter Estimation: AMPC employs algorithms like Recursive Least Squares (RLS) to continuously estimate system parameters. This real-time data integration enables the AMPC controller to adjust and regulate its estimated model and control actions promptly

2. Dynamic Model Updating: The state-space model of the plant beign controlled is updated in real-time, reflecting the latest parameter estimates. This dynamic updating ensures that the predictions used for control are based on the most accurate representation of the system
.

IV.11 Improved Stability

By maintaining accurate and up-to-date control estimated models, AMPC enhances the overall stability of the power system. Stability is a critical concern in power systems, as instability can lead to blackouts and other severe consequences.

1. Enhanced Predictive Accuracy: The predictive accuracy and precision of AMPC models results in more precise control signal, which in turn aide maintaining system stability. More accurately resulting in a reduction of the risks of over- or under-compensation, which can destabilize the system.

2. Feedback Mechanisms: AMPC contains a feedback from the system output to refine its control actions continuously. This feedback loop aims to aide in correcting deviations from the desired trajectory, thereby maintaining system stability

3. Stability Margins: adapting to real-time data, allows AMPC to maintain and even enhance stability margins. This adaptability ensures that the system can stand unforeseen events and maintain stable operation

IV.12 Simulation model :

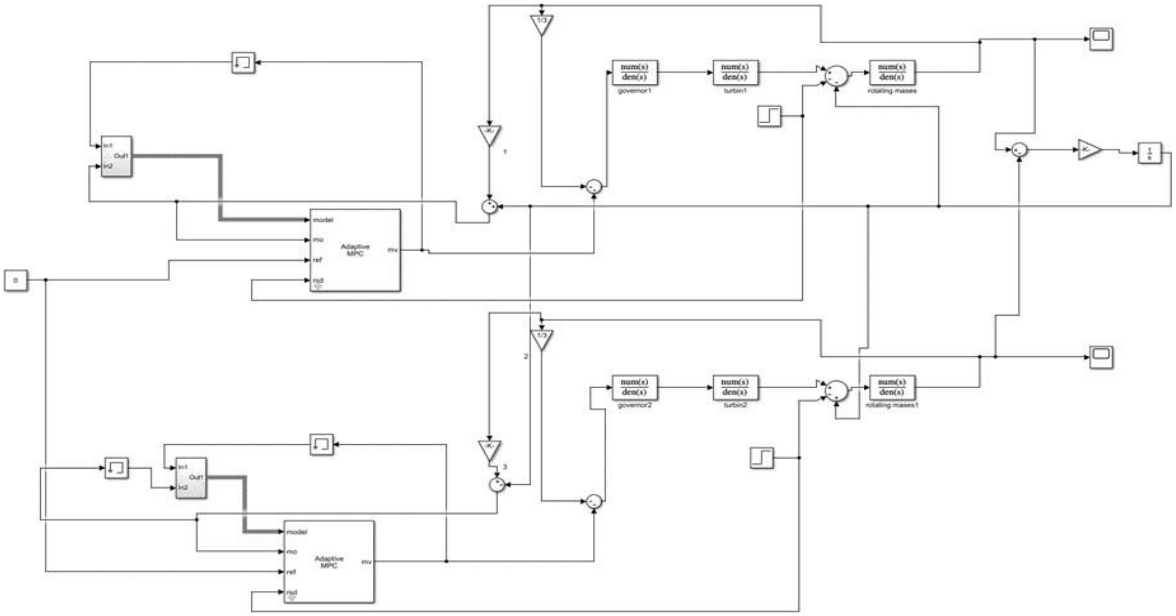


Figure IV.7 : control of a two area power system using a AMPC

IV.13 Conclusion

The adaptive control gains mechanism in AMPC for two-area power system LFC is a powerful tool for maintaining system stability and performance. By continuously updating the system parameters and control gains, the adaptive control strategy ensures robust and optimal operation in the face of changing conditions and uncertainties. The detailed mathematical foundation and workflow provided here illustrate the sophisticated nature of adaptive control gains and their critical role in advanced power system management.

Chapter V

Results and discussion

V. Chapter V: Results and discussions

V.1 Introduction:

In this chapter, we delve into the simulation results obtained from various control techniques implemented in our study. The focus lies on understanding how these techniques respond to fluctuations in load disturbances across different areas. By examining these responses, we aim to gauge the efficacy of the implemented control methods in handling such variations.

Our analysis adopts a comparative approach, juxtaposing the outcomes of different control techniques. While our project predominantly centers around model predictive control (MPC) approaches, we broaden our scope by integrating other methods such as Proportional-Integral-Derivative (PID) control and Nonlinear Autoregressive Moving Average with exogenous inputs (NARMA-L2) control. This inclusion enables us to gain a comprehensive understanding of how diverse control strategies adapt to load fluctuations and discern the disparities between MPC and alternative methodologies.

Throughout the chapter, we meticulously scrutinize the performance metrics derived from each control technique under varying load conditions. By doing so, we elucidate the strengths and weaknesses of each approach, shedding light on their suitability for real world load frequency control applications. Through rigorous analysis and comparison, we aim to provide valuable insights into the efficacy and applicability of different control methods in managing load disturbances effectively.

V.2 PID of three-area power system:

We will be presenting an extensive investigation into the application and performance of Proportional-Integral-Derivative (PID) control in a three-area power system for load frequency regulation. Through meticulous system modeling, dynamic simulation, and detailed analysis, the study aims to provide comprehensive insights into the role and effectiveness of PID control in maintaining system stability, minimizing frequency deviations, and optimizing power exchange among areas under varying load conditions. The paper delves into the design, tuning, and practical implications of PID control for load frequency regulation in multi-area power systems, offering valuable contributions to the field of power system control and operation[28]

V.2.1 Introduction

Efficient load frequency regulation is paramount for ensuring the stability and reliability of interconnected power systems. Control strategies such as Proportional-Integral-Derivative (PID) control have emerged as key tools in achieving this objective due to their simplicity, robustness, and widespread applicability. In this study, we undertake a comprehensive investigation into the application of PID control in a three-area power system, aiming to elucidate its performance, limitations, and practical implications for load frequency regulation.

V.2.2 System Modeling

We will be using the model plant that is previously mentioned in chapter one.

The dynamic behavior of the three-area power system can be described by the following differential equations:

$$\mathbf{x}^{\cdot} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \qquad (V.1)$$

Where:

- **x** is the state vector containing the generator rotor angles, speeds, and tie-line power deviations.
- **u** represents the control input vector comprising the commands to adjust generator outputs.
- **A** and **B** are system matrices representing the dynamics and control inputs, respectively.

V.2.3 PID Controller Design and Implementation

The PID controllers are meticulously designed and implemented to regulate the output of each generator in response to load variations and disturbances. The design process involves selecting appropriate control parameters (proportional gain K_p, integral gain K_i, and derivative gain K) and tuning them to optimize system performance. Various methods, including heuristic approaches and optimization algorithms such as genetic algorithms or particle swarm optimization, may be employed to achieve robust and stable control [29].

The control action (t) of the PID controller is given by:

$$\boldsymbol{u(t) = K_p e(t) + K_i \int_0^t e(r)dr + K_d \frac{de(t)}{dt}} \qquad (V.\ )$$

Where:

- (t) is the error signal representing the difference between the desired and actual values of a controlled variable.

V.2.4 Simulation Setup

The performance of the PID-controlled three-area power system is evaluated through dynamic simulations conducted using specialized software packages as MATLAB/Simulink. The simulations encompass a wide range of operating conditions, including different load scenarios, generation schedules, and system disturbances. Key performance metrics, including frequency deviations, tie-line power imbalances, and controller response times, are analyzed to assess the effectiveness of PID control in maintaining system stability and reliability.

V.2.5 Simulation Results and Analysis

The simulation results provide detailed insights into the dynamic behavior of the PID-controlled three-area power system under various load conditions. Through comprehensive analysis, the study evaluates the performance of PID control in minimizing frequency deviations and optimizing power exchange among areas. Figures depict the transient response of frequency deviations and tie-line power imbalances, highlighting the effectiveness of PID control in maintaining system stability and reliability.

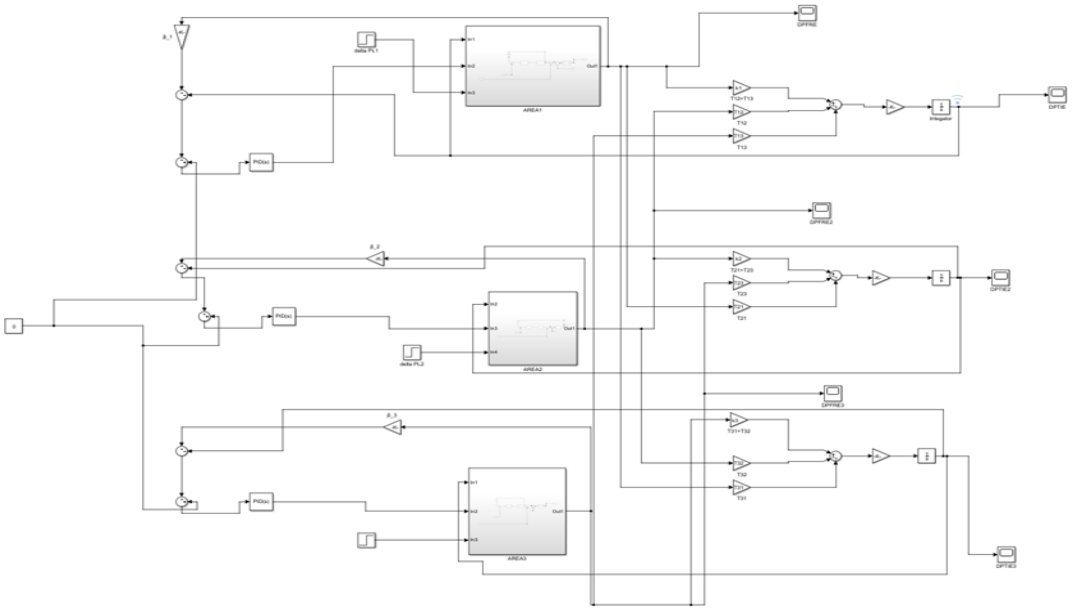


Figure V.2 : PID control of three area power system

V.3Results and discussions

a LMPC results :

LMPC, renowned for its simplicity and effectiveness in power system control, offers robust solutions for various operational scenarios. In this section, we delve into the outcomes achieved through LMPC implementation, highlighting its ability to optimize system performance while adhering to operational constraints.

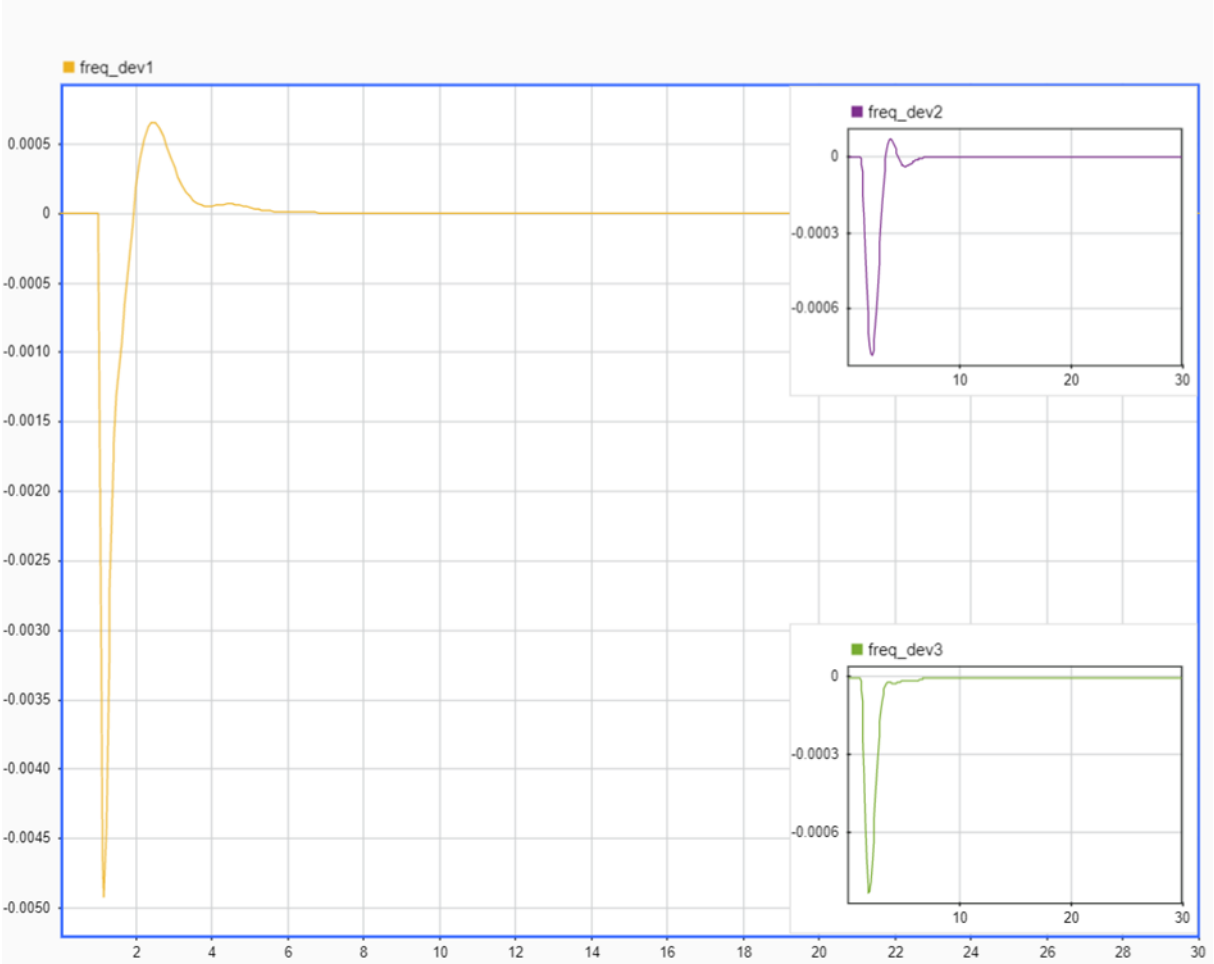


Figure V.3 : frequency deviation after applying 1 percent load on single area of the three area power system

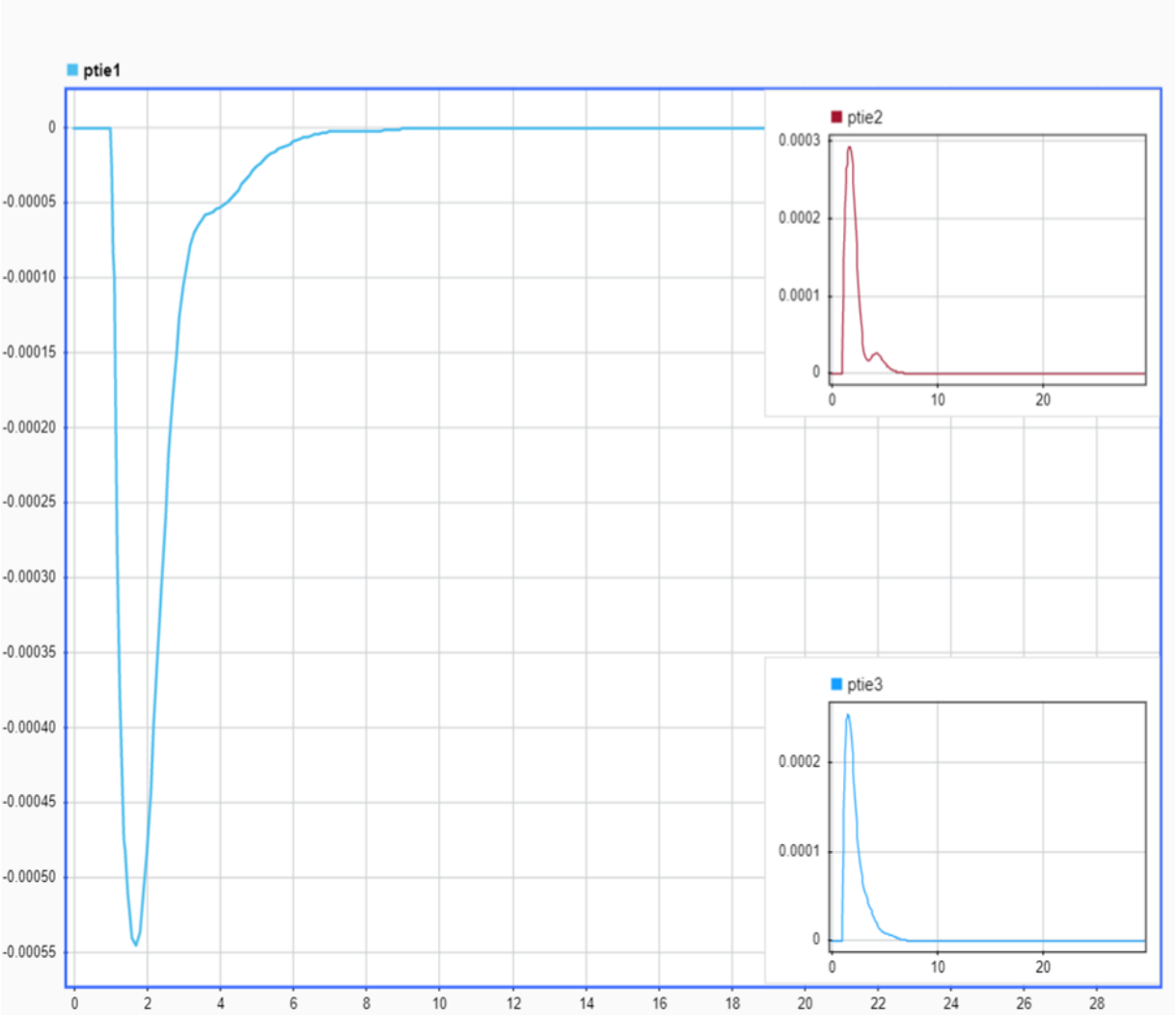


Figure V.4 : change in total power duo to one percent load on the controlled three area power system

b Ampc results :

In dynamic power system environments, adaptability is key to ensuring stability and efficiency. Our investigation into AMPC techniques offers insights into their capacity to dynamically adjust control strategies, thereby accommodating unforeseen disturbances and evolving system conditions. Herein lies our exploration of AMPC results and their implications for real-world application.

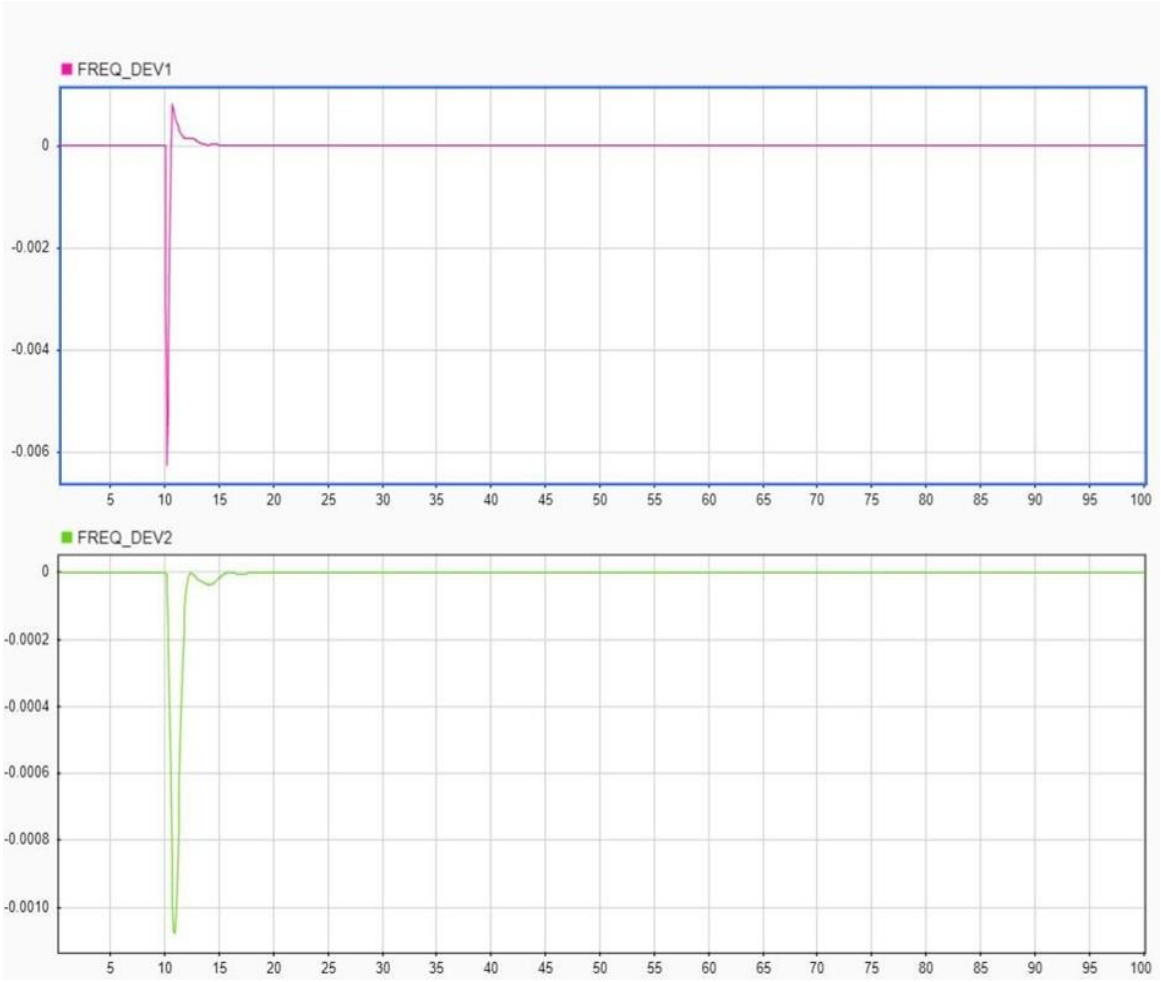


Figure V.5 : frequency variation duo to one percent load on a two area power system

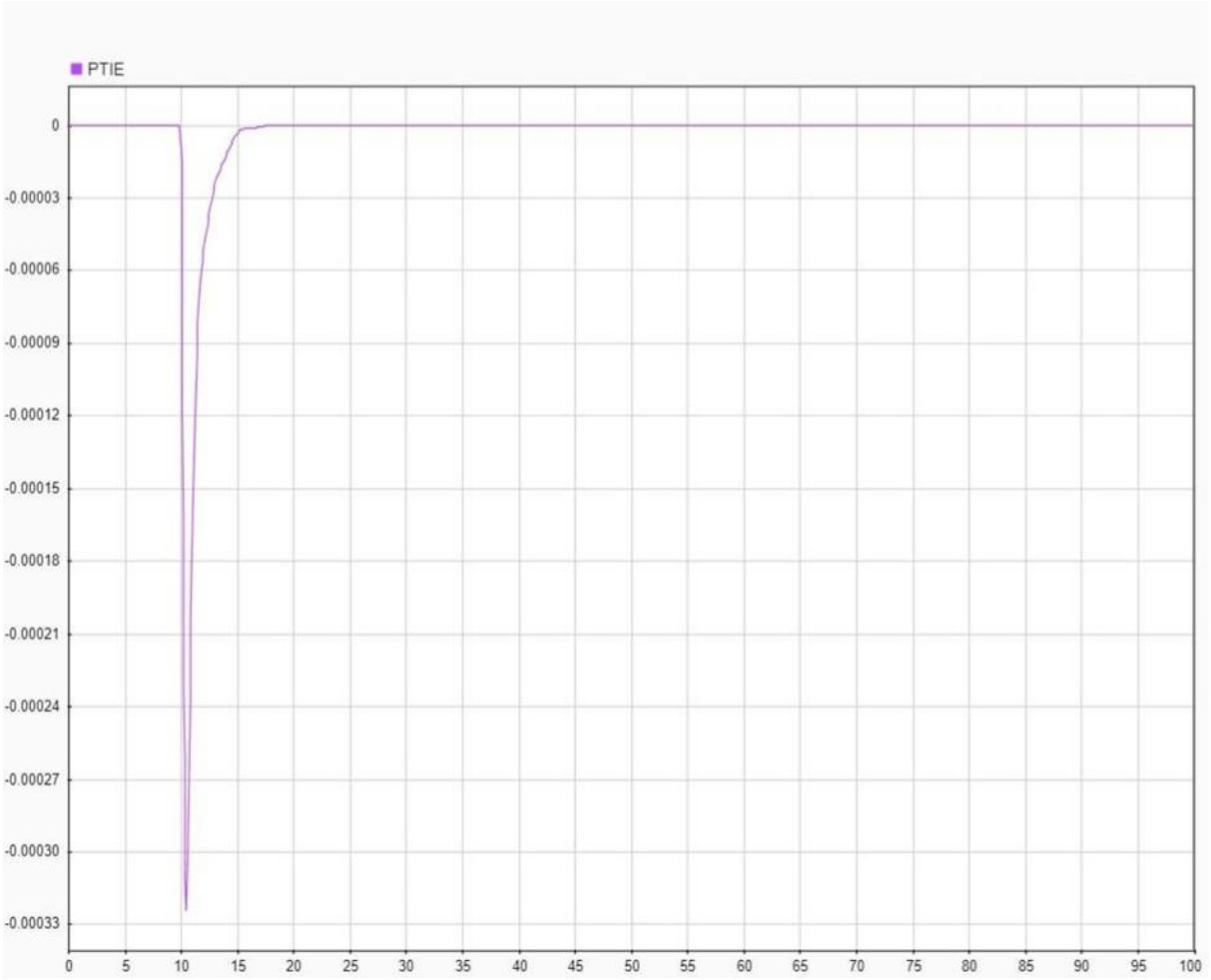


Figure V.6 : change in total power duo to one percent load on a two area power system

c NNPC Result :

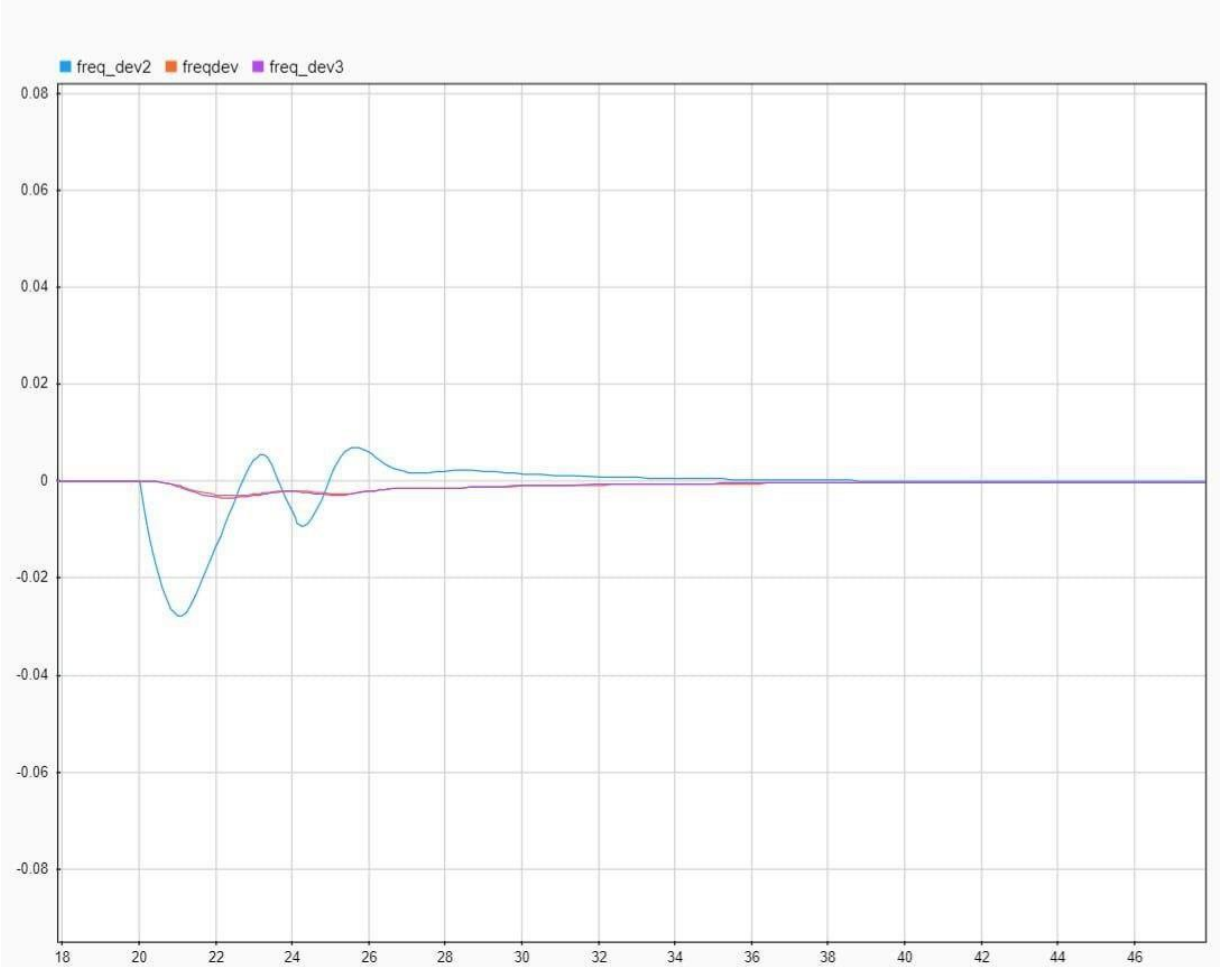


Figure V.7 : frequency deviation duo to one percent load on the controlled three area power system

d PID result :

PID control, a fundamental technique in control systems, is widely used in power systems due to its simplicity and reliability. This method combines three control actions—proportional, integral, and derivative—to achieve desired performance by minimizing errors and ensuring system stability. In this section, we present the results obtained from implementing PID control in our power system model, focusing on its effectiveness in maintaining stability and optimizing system performance.

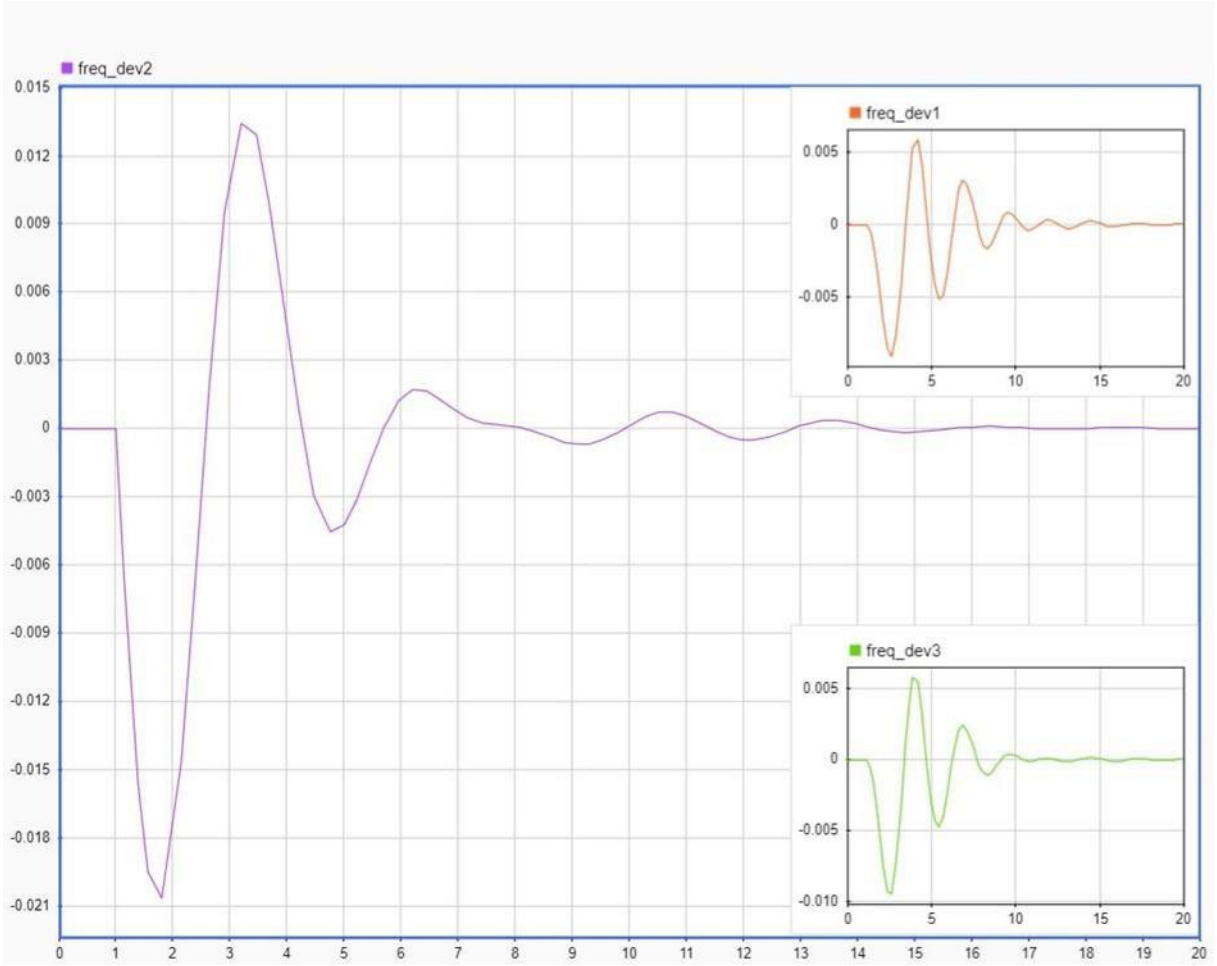


Figure V.8 : frequency deviation of the controlled three area power system

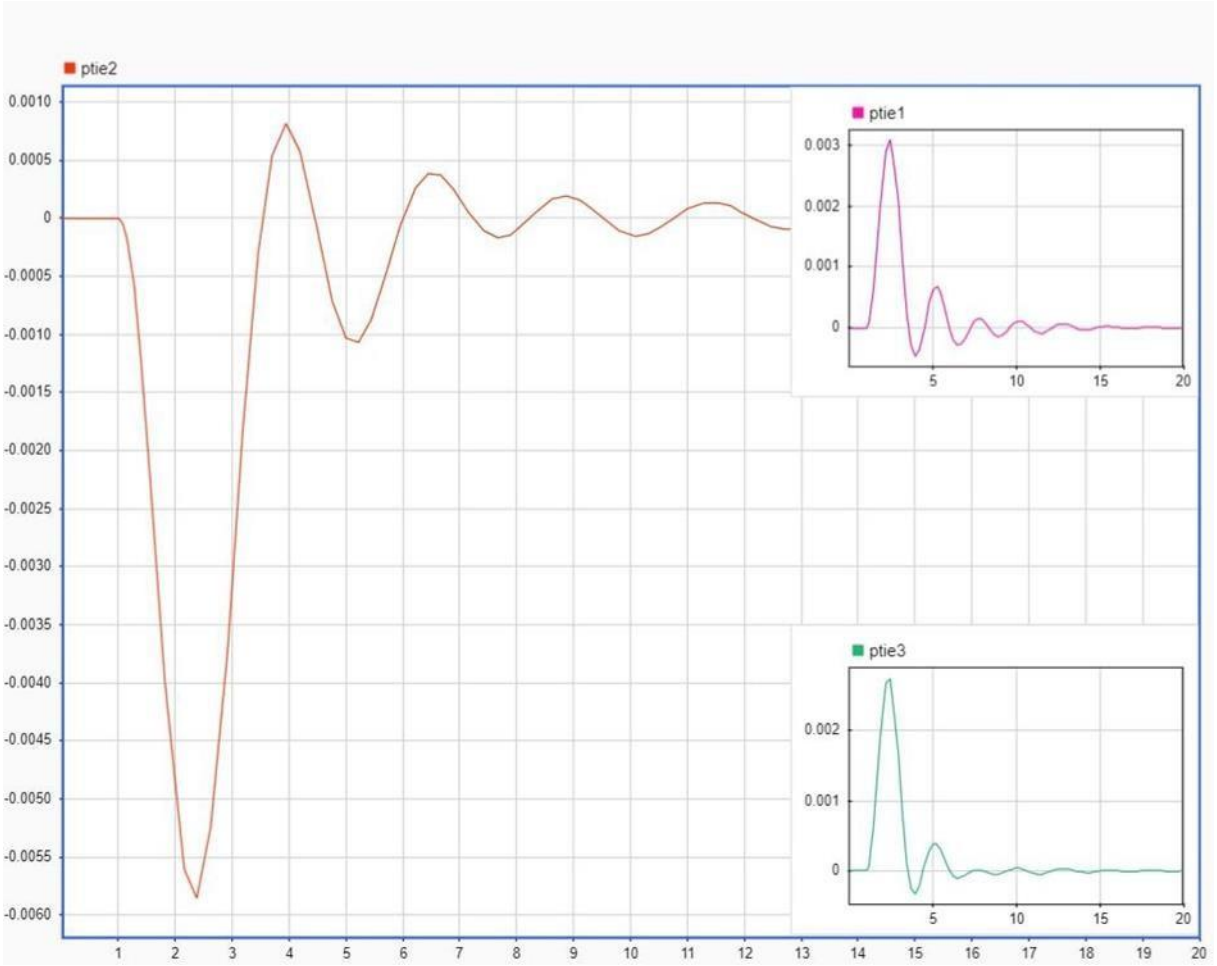


Figure V.9 : change in total power duo to one percent load on the three area power system

V. 4 Comparative Overview :

In this section, we delve into the comparative analysis of various control strategies applied to our power system model, specifically focusing on Linear Model Predictive Control (LMPC), Neural Network Predictive Control (NNPC), Adaptive Model Predictive Control (AMPC), and Proportional-Integral-Derivative (PID) control. Each method's performance is evaluated based on its ability to maintain system stability, response time, and overall efficiency.

a Linear Model Predictive Control (LMPC) :

The implementation of LMPC in our three-area power system has yielded highly satisfactory results, particularly under a one percent load variation. LMPC effectively handles the control objectives by predicting future system states and optimizing control actions accordingly . The key highlights of LMPC's performance are as follows:

- ☑ **Stability**: LMPC maintains system stability exceptionally well, with minimal deviation from the setpoint.
- ☑ **Response Time:** The system exhibits a prompt response to load changes, achieving stability in a timely manner.
- ☑ -**Performance:** Overall, LMPC proves to be robust and efficient in managing the power system dynamics, ensuring smooth and reliable operation.

b Neural Network Predictive Control (NNPC)

Neural Network Predictive Control leverages the adaptive learning capabilities of neural networks to manage power system control . While NNPC performs adequately, it exhibits certain limitations compared to LMPC:

- ☑ **Stability and Convergence:** NNPC achieves stability, but its convergence time is slightly longer compared to LMPC. The system takes more time to settle into a stable state following a disturbance.
- ☑ **Response Time:** The time response of NNPC is slower than that of LMPC, indicating a delay in reaching the desired setpoint.
- ☑ **Adaptability:** Despite its slower response, NNPC offers the advantage of adaptability, as it can learn and adjust to new patterns in the system dynamics over time.

c Adaptive Model Predictive Control (AMPC)

AMPC shows remarkable performance in the two-area power system, demonstrating superior capabilities in both stability and response time. Compared to other methods, AMPC stands out with the following characteristics :

- ☑ **Stability:** AMPC ensures robust system stability, managing to swiftly counteract disturbances and maintain equilibrium.

- ☑ **Response Time:** The response time of AMPC is better than that of NNPC and slightly better than LMPC, making it highly efficient in real-time operations.
- ☑ **Performance:** Overall, AMPC excels in handling dynamic changes in the power system, offering a fine balance between speed and stability.

d Proportional-Integral-Derivative (PID) Control

While PID control is a fundamental and widely used technique in power systems, the results from our study indicate its limitations when compared to advanced predictive control methods :

- ☑ **Oscillations:** PID control results in noticeable oscillations, which compromise the system's stability and performance.
- ☑ **Stability:** The presence of oscillations means that PID control struggles to maintain a stable state, particularly under varying load conditions.
- ☑ **Response Time:** Although PID control offers a quick initial response, the sustained oscillations prevent the system from achieving a smooth and stable state.

V. 5 Comparative Analysis

The comparativee analysis of LMPC, NNPC, AMPC, and PID control methods highlights the distinct advantages and limitations of each approach.

- **LMPC:** Demonstrates excellent stability and a fast response time, making it highly effective for maintaining control in the power system under study.
- **NNPC:** While adaptable and capable of learning from system behavior, NNPC lags behind in terms of response time and convergence to stability compared to LMPC.
- **AMPC:** Outperforms both NNPC and LMPC in the two-area power system setup, offering the best combination of stability and response time. It slightly surpasses LMPC in terms of efficiency.
- **PID:** Despite being a fundamental control technique, PID is outperformed by LMPC, NNPC, and AMPC due to its tendency to induce oscillations and its challenges in maintaining consistent stability.

In conclusion, while each control method has its unique strengths, advanced predictive control techniques like LMPC, NNPC, and AMPC offer superior performance over traditional PID control. Among them, AMPC emerges as the most promising approach, particularly for dynamic and complex power system environments, followed closely by LMPC. NNPC, although slightly slower, remains a valuable method due to its adaptability. PID control, while useful in simpler scenarios, is less effective in the face of modern power system demand

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