Design and Implementatıon of Linear Model Predictive Siso Boost Pressure Controller for a Series Sequential Diesel Engine

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ABSTRACT

This paper focuses on the design and implementation of model predictive controller (MPC) for a boost pressure control of series sequential diesel engine. Boost pressure control is critical to satisfy diesel engine performance and driveability requirements as well as increasing volumetric efficieny. In this study, Control oriented linear models are generated by using system identification methods in order to be used in output prediction models. Prediction models are identified for 5 different engine operating regions to increase the accuracy of linear models. Based on state-space prediction models, Controller design is performed considering Kalman Filter tuning, constraint definitions, controller weights. Engine dynamometer testing have been performed to define input and input rate constraints. MPC design is performed for online optimization method. Nonlinear engine model is modeled in high fidelity simulation environment. Results are shown that MPC is capable of showing better setpoint tracking while satisying contraints explicitly than conventional PID (Proportional-Integral-Derivative) controllers. Relatively easy tuning, ability to handle constraints and incorporation of models makes MPC attractive to Automotive control community.

Keywords: Model predictive control; system identification; Diesel engine control.

Seri Bağlı Aşırı Doldurma Sistemine Sahip Dizel Motorlar İçin Doğrusal Model Tahmini Tabanlı Basınç Kontrolcüsü Tasarımı ve Simülasyonu

ÖZET

Bu makalede seri bağlı aşırı doldurma sistemine sahip bir dizel motor için model tahmini bazlı basınç kontrolcüsü tasarımı ve simülasyonu sunulmuştur. Dizel motorların performans ve sürüş özellikleri geliştirmek ve volumetrik verimi arttırmak için aşırı doldurma basıncının kontrolü kiritk bir önem arzetmektedir. Bu çalışmada ilk olarak, sistem tanıma metodu kullanılarak, kontrolcü tasarımında kullanılacak doğrusal modeller yaratılmıştır. Motorun çalışma bölgesinde 5 ayrı bölge için doğrusal modeller çıkarılmıştır. Çıkarılan bu modeller kullanılarak, Kontrolcü tasarımı gerçekleştirilmiştir. Kontrolcü tasarımında Kalman filtresi ve ağırlıklandırma matrislerinin kalibre edilmesi ile sistem kısıtları belirlenmiştir. Sistem kısıtlarının belirlenmesinde motor dinamometresinde testler gerçekleştirilmiş ve elde edilen veriler giriş ve giriş oranı kısıtlarının belirlenmesinde kullanılmıştır. Kontrolcü tasarımı çevrimiçi eniyileme metodu baz alınarak gerçekleştirilmiştir.. Benzetimlerde, yüksek hassasiyetli doğrusal olmayan motor modeli kullanılmıştır. Sonuçlarda, model tahmini bazlı kontrolcünün, standart PID'lere göre daha üstün set edilen değer takibi yaptığını ve bunu sağlarken sistem kısıtlarını da dikkate aldığı gözlemlenmiştir. Kalibre edilmesinin göreceli olarak kolay oluşu, sistem kısıtlarını tasarımda dahil etmesi ve model bazlı olması nedeniyle Otomotiv kontrolü alanında çekici bir hale gelmiştir.

Anahtar Kelimeler: Model tahmini bazlı kontrol; Sistem tanıma; dizel motor kontrolü.

1. INTRODUCTION (GİRİŞ)

Customer performance and fuel economy requirements as well as environmental concerns (reduction of gaseous and particulate emissions, CO_2) leads progressive development in the field of Automotive Control. Although the challenges are valid for most of the subsytems, powertrain control is emerged thanks to high nonlinear behaviour, fast system dynamics and complexity. Stringent emissions legislations requires extensive control loops with more sensors and actuators added. This phenomena makes the control problem multi-dimensional and multi-variable.

Diesel engine management consists of controlling of fuel, air and exhaust paths. Coordinated control of fuel and air path results in efficient diesel combustion. The amount of fresh inside cylinders is controlled by boost pressure . Increased boost leads to inreased air density therefore higher mean effective pressure which increases power output from the engine. Supercharging increases the amount of boost by employing exhaust-gas

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turbchargers and/or mechanical supercharging units. Series sequential turbocharging refers to the system in which two exhaust gas turbocharges are connected in series in order provide enough boost at rated power and load response at low speed-load points [1].

Current ECU(Engine Control Unit) algorithms incorporate conventional map-based PID controllers for Boost pressure control. Most algorithms include anti-wind up strategies as well as feedforward compensation. These gain scheduled PIDs result in extensive effort to calibrate each map in engine dynamometer and vehicle testing. In addition, system hardware limitations and constraints should be handled indirectly . This is mostly performed by setpoint limitations.

Being developed in process industry in 1980s, Model predictive control offers a formulation to this multivariable problem in terms of constrained finite horizon optimal control problem. Basically, MPC formulation is based on multivariable framework which provides suitable environment for Multi-Input and Multi Output systems [2]. Moreover, soft and hard constraints are handled in this multivariable control framework where the limitations need not to be considered seperately [3]. In addition, optimal control sequence can be either calculated online of explicitly (See [4] for details on Explicit MPC)

The outline of this paper is organized as follows; Section 2 include the derivation of control-oriented model and partition of engine operating region. Section 3 include the MPC formulation. Constraints definition and Kalman filtering is mentioned in Section 3. Section 4 shows the simulation setup as well as the generation of high fidelity engine model in RICARDO WAVE. Section 5 concluded with the simulation results.

2. CONTROL ORIENTED MODEL (KONTROL AMAÇLI MOTOR MODELİ)

The system to be modeled is shown in Figure 1. Test engine is 2L series sequential diesel engine. There are 2 seperate turbocharger units which are connected in series (HP-High Pressure stage and LP-Low Pressure stage). Low-end and high-end torque characteristics of the engine defines the turbocharging matching criteria. At high load-speed points LP turbocharger is more efficient therefore Turbocharger size is matched according to the rated power. HP turbocharger matching is performed according to satisfy better transient characteristics and low-end torque performance only.

Control of boost pressure is performed by means of HP bypass and LP bypass valves. Both of these valves are electropneumatically actuated by ECU. The after treatment parts such as Diesel oxidation catalyst and Diesel Particulate filter have not been considered in this study. Therefore, the LP turbine outlet pressure is assumed equal to atmospheric pressure. Moreover the air filter restriction is not taken into account.

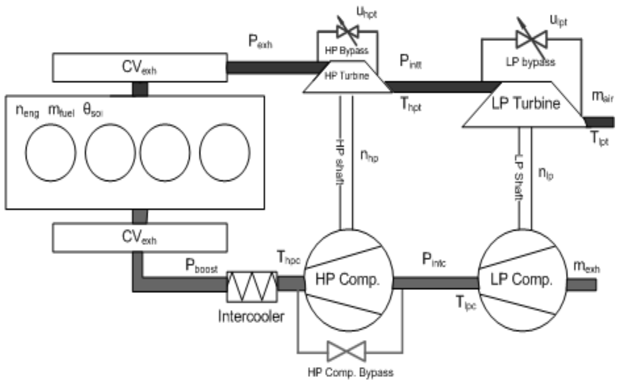

Figure 1: Engine Architecture (Motor mimarisi)

In order to design linear control system, the controlled plant should be represented in linear system formulation. This can be achieved by 2 methods; Linearization of nonlinear gray box models and system identification based black-box modeling. During this study, latter method is used. Linearization of gray-box, mean-value engine models is cumbersome in case high order systems with high number of states. In this case, linear system is identified by using input and output data. Unlike, gray box models, there is no physical relation of black-box model to real engine system but only mathematical relations [5]. Moreover, black-box model derivation can take shorter times, which would be less than theoretical, gray-box modeling method [6].

Generally, there are parametric and non-parametric methods used in system identification. Non-parametric methods are so-called data-based identification [7]. Linear Time-invariant system identification in state-space form by using parametric methods is much more easier and convenient than using non-parametric data-based methods. There are number of parametric methods but during this study, Prediction Error Minimization (PEM) methods and Sub-Space identification methods (N4SID) are used due to being compatible with state-space identification (see [8] and [9] for details on PEM and N4SID methods). In either method, final form of the model is described in terms of state space realization shown in (1).

$$x(t+1) = Ax(t) + Bu(t) + Ke(t) \quad (1)$$

$$\boldsymbol{y(t) = Cx(t) + e(t)}$$

During system identification tests, Pseudo Random Binary Sequence (PRBS) signal is applied to HP bypass valve. PRBS test signal is recommended signal in the literature as they excite the dynamics of all frequencies uniformly, and relatively easy and safe to implement [10]. The term pseudo refers to the fact that the PRBS signal is actually deterministic signal and its autocorrelation function is the same as a white random noise. LP bypass valve is fully closed during experiments. Filtered white noise signal is applied to Injection quantity and engine speed.

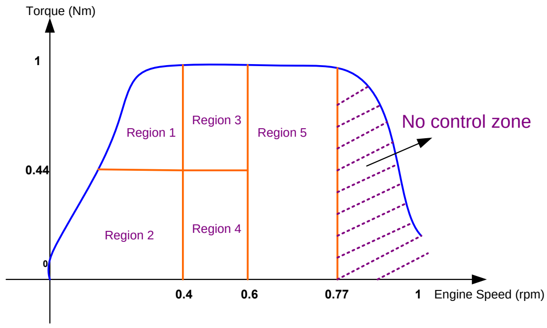

Figure 2. Regions for local linear model across engine operating zone (Doğrusal model için motorun çalışma bölgeleri)

Figure 2 shows the seperation of engine operating and relevant model regions. Regions have been selected according to turbocharger operation and hardware capabilities. Region 2 and region 1 denotes the operating conditions where engine speed is low but the low end torque is high. It is quite likely that during acceleration, turbocharger will operate in this region. Region 2 and region 4 is coinciding with NEDC (New European Driving cycle) emissions cycle. Region 3 is the intermediate region which is critical in boost pressure control. Corrected mass flows and compressor/turbine efficiencies are high in this section. It should be noted that there is a "no-control zone" in which controller is not activated.It is quite unlikely that transient conditions is occurred in this zone as the engine speed is high but the torque is low.

Local linear models are generated for each of the regions shown in Figure 2 by using system identification methods mentioned above. Experiments are performed in transient engine dynamometer. Figure5 shows the workflow that has been followed during identification process.

Identification results of local linear model for region 3 is shown in Figure 4. Although the model fit performances are similar between N4SID and PEM methods, N4SID method is slightly better than PEM. This is clear in Table 1 which includes the main statistical variables for PEM and N4SID models. N4SID shows better performance as the 3σ (3 times standard deviation) separation is 80.23 hPa where PEM shows 141 hPa separation.

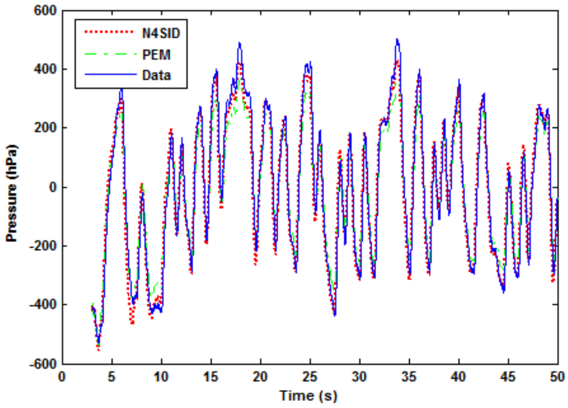

Figure 4: SISO model validation results for Region 3 (3.bölge için SISO model doğrulanmasına ait sonuçlar)

3. CONTROLLER DESIGN (KONTROLCÜ TASARIMI)

Explicit use of models during control design, improves controller sensitivity to disturbances as well as providing better setpoint tracking capability. Literature

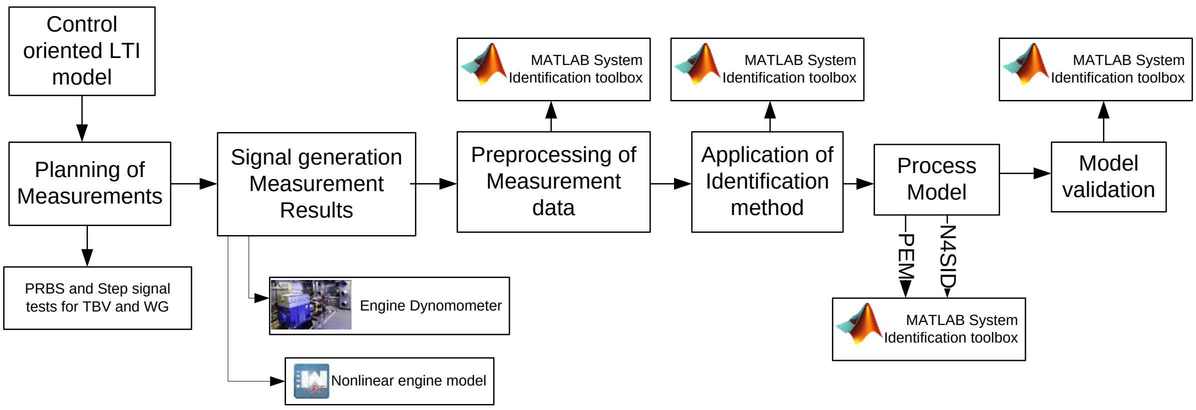

Figure 5: System identification workflow (Sistem tanıma iş akışı)

Table 1: N4SID method and PEM statistical variables for Region 3(N4SID ve PEM modellerinin istatistiksel sonuçları).

Identification method	Standard Deviation (mbar)	3xStandard Deviation (mbar)	Mean (mbar)	Min (mbar)	Max (mbar)
N4SID	26.79	80.37	5.43	-61.17	96.17
PEM	47.03	147	6.334	-89.87	139.3

search have been focused on model-based controllers schemes due to ability to incorporate system dynamics to controller synthesis. In the literature, there are variety of model based controllers but during this study, research have been focused on MPC design.

3.1 MPC Formulation (MPC Formülasyonu)

Online computation of future manipulated variables to optimize the future behavior of the outputs is the MPC's main design objective. The term "Prediction" in MPC definition denotes the prediction of future output trajectories.

Basically, at each time step, finite horizon open-loop optimal control problem is solved online. Optimization yields an optimal control sequence. Please keep in mind that MPC is a family of controller . It is not designating a specific controller but explains the range of methods. Various MPC controllers are separated according to the

$$min \sum_{k=0}^{N-1} \left[y_{t+k|t} - r(t)\right]^T Q\left[y_{t+k|t} - r(t)\right] + \delta u_{t+k|t}^T R \delta u_{t+k|t}$$

$$s.t.$$

$$\begin{aligned}
y_{\min} &\leq y_{t+k|t} \leq y_{\max} \quad , \quad k = 1, \dots, N_c \\
u_{\min} &\leq u_{t+k} \leq u_{\max} \quad , \quad k = 1, \dots, N_c \\
\delta u_{\min} &\leq \delta u_{t+k} \leq \delta u_{\max} \quad , \quad k = 1, \dots, N_u - 1 \\
x_{t+k+1|t} &= Ax_{t+k|t} + Bu_{t+k}, k \geq 0, \\
y_{t+k|t} &= Cx_{t+k|t}, k \geq 0, \\
u_{t+k} &= u_{t+k-1} + \delta u_{t+k}, k \geq 0, \\
\delta u_{t+k} &= 0, k \geq N_u
\end{aligned}$$

(3)

Here $Q \geq 0, R \geq 0$ are the positive semidefinite output and input weightings where $u_{\min}$, $u_{\max,}$ $y_{\min}$, $y_{\max}$, $\delta u_{\min}$, $\delta u_{\max}$ are the input,

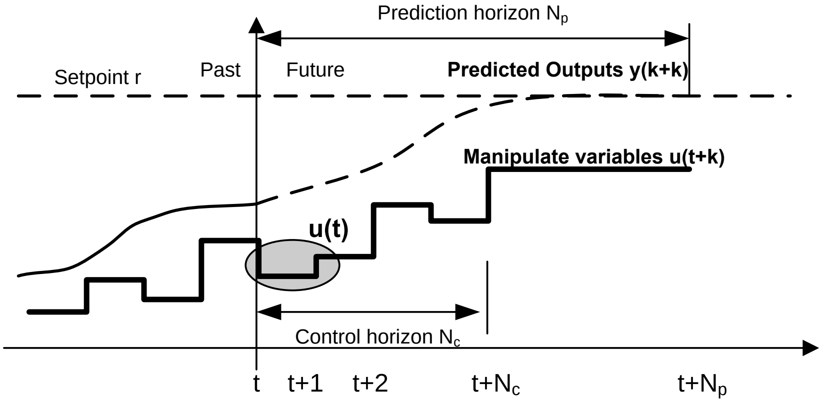

Figure 6: MPC srategy (MPC kontrol stratejisi)

plant model types, noises and cost function used in optimization [11]. MPC has become attractive especially for linear processes. Linear models are used in Linear MPC family in order to represent the system dynamics although the real dynamics of the system is non-linear. Linear MPC formulation is well addressed across industry and research community and proved the performance in terms of performance, stability and online-computation requirements.

Suppose a linear time invariant discrete-time system as shown in (2)

$$x_{k+1} = Ax_k + Bu_k \qquad (2)$$

$$y_k = Cx_k$$

Where, $x_k \in \mathrm{R}^n$ is the state vector and $u_k \in \mathrm{R}^m$ is the input vector (mainly indicated as manipulated variables) which is the output of solution of optimal control problem.

Constrained finite horizon optimal control problem can be stated for output reference tracking problem as shown in (3). Optimal control problem is constructed as quadratic program with linear constraints.

output and input rate constraints. N is the prediction horizon in which the optimization takes place. At time *t* , current state is estimated or measured and the QP problem is solved for *N* steps to get an optimal control of future input defined as $U^*(x(t))$. Apply only,

$$u(t) = u_0^*(x(t) \qquad (4)$$

Remaining control input for control horizon are not taken into account and iterative process is repeated at time *t+1*.

System model can be extended by including the measured and unmeasured disturbances. Measured disturbances are mainly exogenous inputs which have direct effect on system response but there is no control applied. For example, engine speed and injection quantity affects the boost pressure because the fuel and air setpoints are changed. Unmeasured disturbances may appear in forms of sensor noise, model prediction errors as well as input disturbances. Extended system model covering measured and unmeasured disturbances is shown in (5).

$$x_{k+1} = Ax_k + Bu_k + B_v v(t) + B_d d(t) \qquad (5)$$

$$y_k = Cx_k + D_v v(t) + D_d d(t)$$

Where $v(k)$ is the measured disturbances, $d(k)$ is the unmeasured disturbances which covers both state disturbances defined by B_d and output disturbances D_d .Disturbance model is totaly application dependent. During this study, disturbance model suggested by [13] has been implemented. It is basically modeled as shown in (6) below.

$$x_d(k+1) = \bar{A}x_d(k) + \bar{B}n_d(k) \qquad (6)$$
$$d(k) = \bar{C}x_d(k) + \bar{D}n_d(k))$$

Where $n_d(k)$ is zero-mean, unit variance, random Gaussian input and $x_d(k)$ is the input disturbance states. Basically, unmeasured disturbances are also representing modeling errors. Measurement noise model also implemented in a similar way.

By combining (5) and (6) we will have the extended state vector $[x'(t) \quad x_d{}'(t)]$ described in (7) below.

$$\begin{bmatrix} x(k+1) \\ x_d(k+1) \end{bmatrix} = \begin{bmatrix} A & B_d\bar{C} \\ 0 & \bar{A} \end{bmatrix} \begin{bmatrix} x(k) \\ x_d(k) \end{bmatrix} + \begin{bmatrix} B_u \\ 0 \end{bmatrix} u(k) + \begin{bmatrix} B_v \\ 0 \end{bmatrix} v(k) + \begin{bmatrix} 0 & B_u & B_v \\ \bar{B} & 0 & 0 \end{bmatrix} \begin{bmatrix} n_d(k) \\ n_u(k) \\ n_v(k) \end{bmatrix}$$

$$y(k) = [C \quad \bar{C}] \begin{bmatrix} x(k) \\ x_d(k) \end{bmatrix} \qquad (7)$$

It should be noted that $\bar{D}$, D_{du}, D_{dv} is assumed to be zero through the formulations.In addition $n_u(k)$ and $n_v(k)$ are the unmeasured disturbances applied to manipulated variables and measured disturbances which are also modeled as zero-mean, unit covariance white noise signals. Some of the states cannot be measured depending on the model information. System identification based models includes some states which combination of physical states. These states cannot be measured but rather are estimated. In this case, linear state observer should be used for state estimation. Please note that the necessary and sufficient condition for observer design is that, combined state space model in (6) should be observable. Linear state estimator is used to estimate combined state vector $[x_d(k+1) \quad x(k+1)]^T$ by using measured output values. During this study, Kalman filter is designed as a linear state estimator. State estimation of Discrete time Kalman filter is generic with linear state estimation formulation.

$$\hat{x}(k+1|k) = A\hat{x}(k-1|k) + B\Delta u(k) + M(y(k) - Cx(k-1|k)) \qquad (8)$$

Where L is the observe gain matrix which is expressed as product of A and M. The gain matrix L is derived by solving a discrete Riccati equation.

3.2 Control Objectives (Kontrolcü tasarım kriterleri)

Two-stage turbocharged system should satisfy certain performance criteria. In this case, performance criteria can be defined in terms of the transient response of the system and the tracking of optimized steady state set points. As mentioned in [12], Diesel engine torque response is proportional to intake manifold pressure gradient. During controller design, system's performance should be assessed by using predefined transient response criteria. Controller objectives are summarized below.

1. Primary goal is to track the desired boost pressure shown as red line in Figure 7 at constant engine speed.
2. The maximum system characteristics to increase the boost pressure is experimented by setting both HP and LP bypass valves to fully closed positions. This will give us the physical limitation of the system. This is shown in green dash-dot line in Figure 6.
3. The overshoot of boost pressure should be limited to the values shown in Table 2 according to the varying steps in intake pressure.

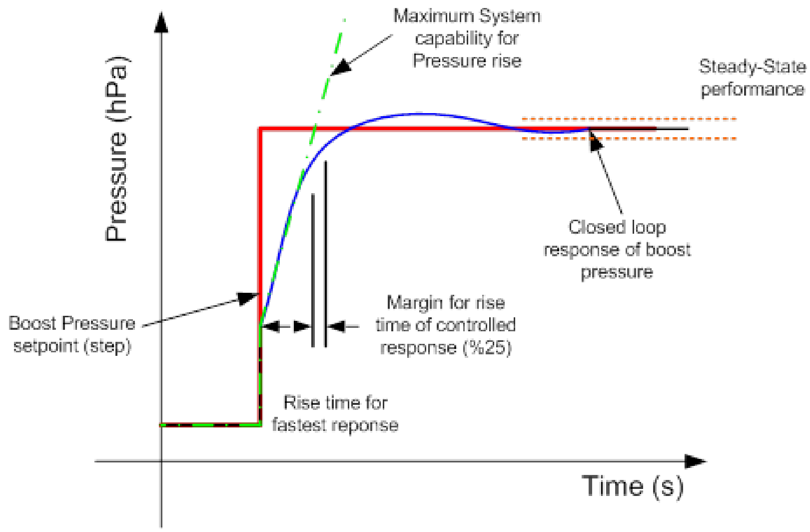

Figure 7: Transient response characteristics(Geçici rejim cevabı)

Table 2: Transient response time requirements for varying pressure steps (Değişken basamak basınç girişleri için geçici rejim cevabı hedef değerleri)

Step Signal (mbar)	Rise/Fall Time (ms)	Nominal Over/Undershoot	Steady-State Accuracy
100	1600	%6	%2.5
250	2100	%7	%2.5
500	2400	%8	%2.5

3.3 Specification of Prediction and Control Horizons

(Tahmin ve Kontrol aralıklarının belirlenmesi)

Prediction horizon (PH) defines the optimization window therefore system response is affected directly. Under the situation in which sufficiently longer prediction horizon is used, potential constraints can well be considered and avoided. Also increasing the prediction horizon will have positive effects on controller performance when the plant shows non-minimum phase-behavior. Figure 8b shows the comparison of different prediction horizons. First simulation is performed with Prediction horizon set to 5 samplings and latter was set to 50 samplings. The rise time of boost pressure response is higher when PH is set to 50. But the disturbance rejection and robustness is better than smaller PH's. Control horizon is suggested to be set as some values in between 1 and 6.

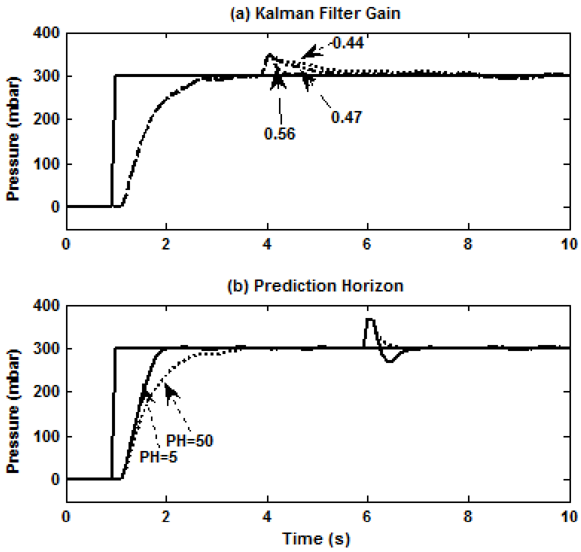

Figure 8: Effect of Prediction horizon and Kalman Filter gain tuning on controller performance (Tahmin aralığı ve Kalman filtresinin kontrolcü performansına etkisi)

During this study, the methodology suggested by [13] has been used.

1. Control interval is based on the system's settling time. Maximum HP bypass valve step command has been applied to observe system's settling time. It was recorded as 4 seconds approximately. Therefore control interval is selected as 0.1 seconds.

2. Prediction horizon is set as number of sampling periods used in step 1 as 30. Decreasing this value should be avoided considering the system has pure time delay and exhibits non-minimum phase behavior.

3. Control horizon is set as 3. Increasing control horizon will have a relaxation on number of free moves thus explicit MPC computation. Therefore, control horizon should be selected as small as possible.

3.4. Controller Weights and Estimator Tuning

(Kontrolcü Ağırlıkları Ve Gözleyici Ayarlanması)

As shown in (3), Q and R matrices are used for weighing the cost function for output set point tracking as well as satisfying input rate constraints to prevent drastic changes in the control signal. Boost pressure output tracking is adjusted by matrix Q and controller adjustments are weighted by matrix R. Please note that the effect of output and input rate weights are contradicting with each other. Increasing R matrix will result in smaller HP bypass valve's controller actions which would increase the controller robustness to boost pressure prediction inaccuracies while degrading set point tracking.

Estimator tuning is basically based on the adjustment of Kalman gain matrix, M. Estimator tuning is as much critical as controller design, as it defines the controller sensitivity to unmeasured disturbances (prediction errors). During controller design, estimator tuning is performed in MATLAB Model predictive control toolbox. Figure 8a shows the effect of Kalman gain matrix on MPC's disturbance rejection capability. During the simulations, overall gain of estimator is changed from 0.44 to 0.56. 50 mbar unmeasured disturbances is applied on boost pressure at 4 sec. with boost pressure set point value is stepped to 300 hPa.

3.5. Constraint Definition (Sistem Kısıtlarının Belirlenmesi)

As critical part of the finite horizon optimal control problem, constraint definition should be clearly determined during controller design process. Constraints are mostly related with physical system. Output constraints are considered as 1^{st} type which is directly related with the system dynamics. During this study, the single output and the controlled variable is the boost pressure. Constraint definition for boost pressure is required especially for maximum values in order to prevent cylinder failure. The dynamics of thermal and mechanical stress induced by boost pressure [1]. As the boost pressure increased, there should be increase in the peak fire pressure and compression end pressure. These would increase the mechanical strength applied on the connecting rod, piston, cylinder head and bearings. There should be design limit for over boost which would prevent the engine components failed. During this study, the upper limit for boost pressure is set as 3500 mbar, which slightly lower than the design limit.

There is not any lower limit for boost pressure. Therefore it is set a 0 as shown in (10).

$$\begin{bmatrix} y_{\max} \\ y_{\min} \end{bmatrix} = \begin{bmatrix} 3500 \\ 0 \end{bmatrix} \quad (10)$$

The second type of constraints is the input constraints. HP bypass valve is actuated by vacuum pressure actuator which is mechanically connected to the bypass valve. The source of the pressure inside the actuator is the vacuum pressure blender solenoid. This solenoid is controlled by PWM (Pulse Width Modulation) signal sent by ECU. As the Duty cycle of the PWM signal increases the amount of vacuum applied by solenoid is decreases so the valve is more likely to close. Closed valve results in increase in the turbocharger activity and boost pressure. . PWM is sent by ECU by using internal low-side drivers. Thus input signal constraints are taken directly as the maximum and minimum realizable PWM limits sent by the driver.

$$\begin{bmatrix} u_{\max\,tbv} \\ u_{\min\,tbv} \end{bmatrix} = \begin{bmatrix} 90 \\ 0 \end{bmatrix} \quad (11)$$

Third and the last type of constraints are the input rate constraints. Basically they are related with speed of the actuator. During this study the maximum and minimum rate of the Bypass valve is defined by using engine dyno experiment. Maximum rise of actuator is defined by sending PWM signal by applying maximum Duty Cycle. . This would allow to observe the rate of change of actuator control signal.

4. NONLINEAR ENGINE MODEL (DOĞRUSAL OLMAYAN MOTOR MODELİ)

Nonlinear engine model is generated by using 3rd party package program, RICARDO WAVE RT. The modeling methodology used by WAVE-RT is physical based, crank-resolved model. The modeling scheme is using one-dimensional dynamics of the fluid flow. The capacitive and inertial properties of the fluid in the manifold and engine are seperated, meaning that capacitive properties (mass, pressure, temperature) are concentrated in finite volumes (capacities) while inertial properties (mass and energy flows) are taken into account in the duct branches connecting the capacities. [14]

Figure 9 shows the steady-state and transient validation of WAVE RT model for boost pressure. Relative errors are generally below %10 which is sufficient to use model for engine control purposes. For steady state validation, mean relative error is %1.06. Maximum error occurs operating points in which turbocharger speed are relatively low. Compressor mass flow rate estimation accuracy is lower in those points that correspond to reduction in volumetric efficiency thus manifold pressure. Transient validation shows absolute mean relative error of % 4.45 and maximum absolute relative error of % 6.64. It is essential to mention that model has steady state error, which can be priotirized as low because steady-state error can be eliminated by controller design.

5. SIMULATION-EXPERIMENTAL RESULTS (BENZETİM-DENEYSEL SONUÇLAR)

As the nonlinear model is validated, MPC controller is tested in terms of offline simulations. During simulations, MATLAB-SIMULINK is used. Controllers were designed by using MATLAB RT model in SIMULINK. Fixed step simulation were performed with step time of 1 ms.

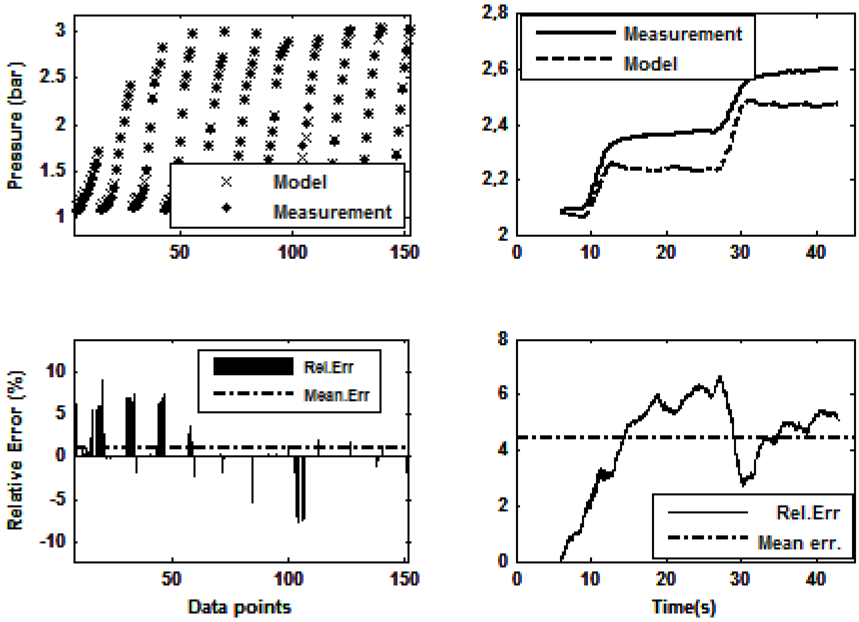

Figure 9: Nonlinear engine model validation (Doğrusal olmayan motor modelinin doğrulanması).

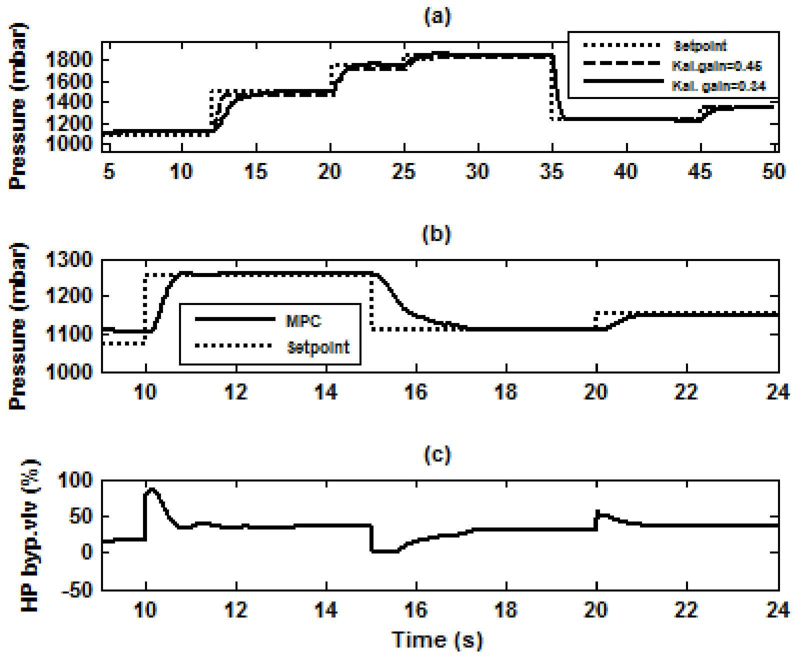

Figure 10: MPC Step signal simulation result (MPC kontrolcüsünün basamak girişi benzetimi)

Figure 10a shows the step response simulation results in which variable steps are applied as boost pressure setpoints. First simulations were performed with Initial Kalman filter gain of 0.45, but due to having steady state error, Kalman filter gain is modified with 0.34 to ensure that zero-steady state error tracking occurred. The rise time for 500 mbar step response is 1.8 seconds which satisfies controller objectives. Small step response results are shown in Figure 9b with controller signal in Figure 9c. The rise time for small steps are below 1.5 seconds which are below limit values. In addition, pressure overshoots are minimized to %1-2.

Figure 11 shows the experimental results when using real-world drive cycle. The cycle includes transient maneouvers which are crucial to assess controller transient response. MPC controller shows better seperation over conventional PID controllers such that standard deviation of boost pressure is 240 mbars where conventional PIDs shows 290 mbars. Moreover, rise time of MPC controller is smaller when there is a step-like boost pressure setpoint.

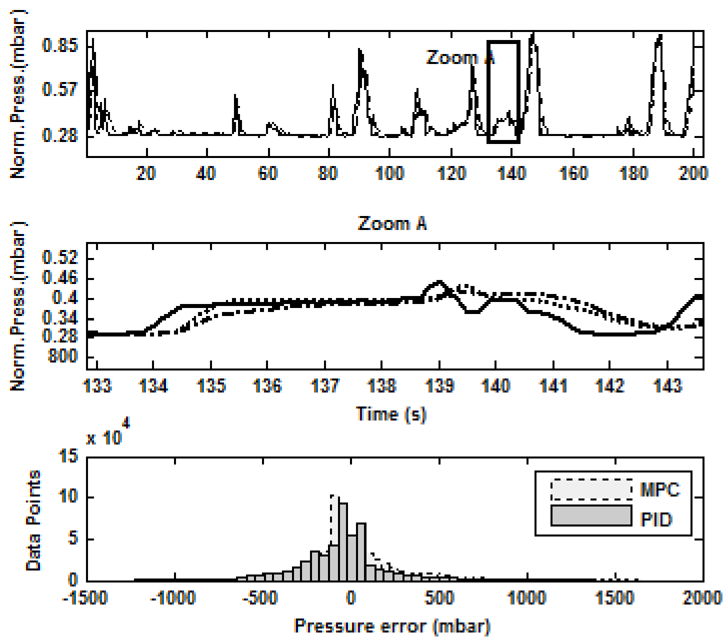

Figure 11: Experimental results from real world driving (Gerçek sürüş koşulları için deneysel sonuçlar)

6. CONCLUSIONS (SONUÇLAR)

This study introduces the Model Predictive Control design to satisfy boost pressure control requirements for a series sequential turbocharged diesel engine. Linear models are generated based on system identification principles. As it is impossible that a single linear model can represent whole engine operating points, linear models are formed for 5 different engine operating regions. Controller design is based on 3 main points; defining prediction and control horizons, tuning of Kalman filter, constraint definitions and finaly weighting matrices. The effect of each factor is defined by series of simulations and engine dyno experiments. Initial controller design are tested by using high fidelity non-linear engine model. Simulation and experimental results were used to demonstrate the effectiveness of the proposed method.. Further study will include real-time test results performed in engine dynamometer or vehicle testing. In addition, utilization of Multi-Input Multi Output (MIMO) control framework by introducing LP bypass valve is ongoing research.

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