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Analysis of Explicit Model Predictive Control for Track-Following Servo Control of Lunar Gravity Compensation Facility

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Abstract: The Lunar Gravity Compensation Facility (LGCF) is a critical component in ground tests for a crewed lunar roving vehicle (CLRV). The track-following servo subsystem's performance is of critical importance in the LGCF, as it needs to achieve high-precision tracking of the CLRV's fast, wide range of motion in the horizontal direction. The subsystem must also operate within various constraints, including those related to speed, acceleration, and position. These requirements introduce new challenges to both the design and control of the subsystem. To tackle these challenges, this paper employs a Permanent-Magnet Synchronous Motor (PMSM) vector control method based on Space Vector Pulse Width Modulation (SVPWM) to achieve accurate speed tracking. Additionally, this paper presents an Explicit Model Predictive Control (EMPC) strategy for precise position servo control of the track-following system under multi-parameter constraints. The simulation model of the track-following servo subsystem is established based on the above methods. The simulation results demonstrate that the position tracking error of the gravity compensation system, constructed using the above method combined with EMPC control, is less than 0.2 m. The control performance of the EMPC is significantly better than those of the PI and LQI controllers. The influence of errors on the drawbar pull is within 12.5%, and its effect on the compensation force is negligible. These results provide theoretical support for the design of a track-following servo subsystem.

Keywords: lunar gravity compensation facility; track-following servo subsystem; PMSM; explicit MPC



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1. Introduction

The crewed lunar roving vehicle (CLRV) is essential in Chinese plans to build a lunar base. The CLRV is an essential and indispensable exploration tool that not only transports astronauts to great distances from the lunar module but also ensures their safety as they move on the lunar surface [1]. To mitigate the potential issues of the CLRV, it is imperative to conduct a comprehensive ground test of the full rover before launch. Furthermore, the differences in gravity between the Moon and Earth give rise to distinct steering properties and driving sensations for the astronauts using the CLRV. Therefore, it is essential to construct a ground test facility on Earth that accurately simulates lunar gravity to facilitate astronaut training and evaluate the CLRV's performance.

A problem common to the ground test facility is simulating a low-gravity environment similar to the spacecraft's natural working environment [2]. Simulating a low-gravity field is an essential issue in the motion performance experiment of the planetary rover. The simulation method of offsetting part of the lunar rover's gravity by an external force is called gravity compensation. The primary ways to achieve artificial micro-gravity include free-fall testing [3], the air-bearing table [4], neutral buoyancy [5,6], and the suspension system [7,8]. Among the available methods, the suspension system [9,10] is widely adopted because of its relatively simple structure, easy construction, and 3-D simulation with unlimited time.

The track-following servo subsystem is a critical component of the suspension gravity compensation system, which is used to precisely track the movement of the test object in the horizontal direction. In the suspension gravity compensation system of the CLRV, due to the large motion velocity, acceleration, and range of the CLRV, the track-following servo subsystem also requires a corresponding motion capability and a large scale. In this context, the crane as the servo motion mechanism exhibits significant inertial characteristics [11]. At the same time, the subsystem is also faced with various constraints such as speed, acceleration, and position. These characteristics often result in significant tracking errors and even control failure.

Currently, research on the effectiveness of the track-following servo subsystem in the suspension gravity compensation system of the CLRV remains unexplored. The active response gravity offload system (ARGOS) at NASA's Johnson Space Center is a typical suspension system [12]. However, the track-following servo subsystem of this system is only applicable for walking tests of astronauts with low velocity in a single direction. The Harbin Institute of Technology built a suspension lunar gravity compensation system, which was only suitable for slow-moving unmanned lunar rovers [2]. The max speed of the Yutu lunar rover is about 200 m/h, while the theoretical maximum speed of the CLRV in pre-research is about 4 m/s. The Soviet Union's planetary rover ground test used an active tracking constant tension suspension scheme [13], which generated a constant vertical pulling force using a parallelogram with a spring. However, this solution is only suitable for ground tests on Mars rovers and may not work well for driving a large vehicle on simulated soft lunar soil. NASA proposed a suspension system scheme suitable for CLRV ground tests in the last century, but the track-following servo control in the program lacks simulation validation and practical implementation [14]. The suspended gravity compensation system is more commonly used in slow-motion microgravity experiments, such as deployable antennas [7] and satellites [8], and its tracking servo subsystem is not suitable for the CLRV.

To meet the CLRV's test requirements, this paper conducts research on the system design and control scheme of the track-following servo subsystem in an overhead-crane-like Lunar Gravity Compensation facility (LGCF) based on a single-cable gravity compensation system. As shown in Figure 1, the system compensates 5/6 of the CLRV's weight over a square test field of 80×20 square meters. As shown in Figure 1, the primary research of this paper is the track-following servo subsystem in the LGCF, consisting of an overhead moving crane and a trolley. The crane moves on the bridge, tracking the real-time position of the CLRV in the X direction, and the trolley moves along the crane girder to follow the real-time Y position of the CLRV. The servo motors drive the crane and trolley.

The paper introduces the vector control of the PMSM to the track-following servo subsystem, enabling high-precision and rapid tracking control. In servo motors, the permanent-magnet synchronous motor (PMSM) has many outstanding advantages compared with other motors. The PMSM vector control system can achieve high precision, high dynamic performance, and an extensive range of speed regulation, tracking, and control, attracting wide attention and research from scholars worldwide [15–17].

This track-following servo subsystem includes the position servo closed-loop and closed-loop control of the motor speed and current. In the simulation model of the speed and current closed-loop control, the surface-mounted PMSM (SPMSM) vector control system based on the Space Vector Pulse Width Modulation (SVPWM) method was used in the paper [18], which highly simulated the actual system. The PI method was used for the PMSM vector control system.

In the position servo closed-loop, there are constraints on the movement speed and acceleration of the crane and trolley to avoid motor idling [19] or over-speed. Moreover, the motion ranges of the crane and trolley are also constrained by the size of the facility. The traditional PID control cannot meet the control requirements, due to multi-variable constraints in the position servo closed-loop. In particular, this paper employs the explicit model predictive controller (EMPC) [20] in the position servo closed-loop so that the

overhead moving crane and the trolley follow the motion of the CLRV in the X and Y directions, respectively. The MPC is a new computer optimization control algorithm that can effectively deal with multi-variable constraint systems [21]. It has become a standard optimization method for complex constraint systems. In recent years, the MPC has received significant attention in path tracking and fast tracking [22,23]. The main reason is that the MPC can better handle the constraints of concern to physical and safety systems, which benefits system control performance and component protection. Despite the advantages of the MPC mentioned above, its substantial computational complexity resulting from online optimization at each sampling time poses a significant drawback and limits its applicability to relatively small and slow systems. To address this challenge, Bemporad and Alberto et al. proposed a novel approach based on an MPC scheme that moves all computational efforts offline, enabling the scheme to overcome the aforementioned limitation [24,25], and the method is the EMPC.

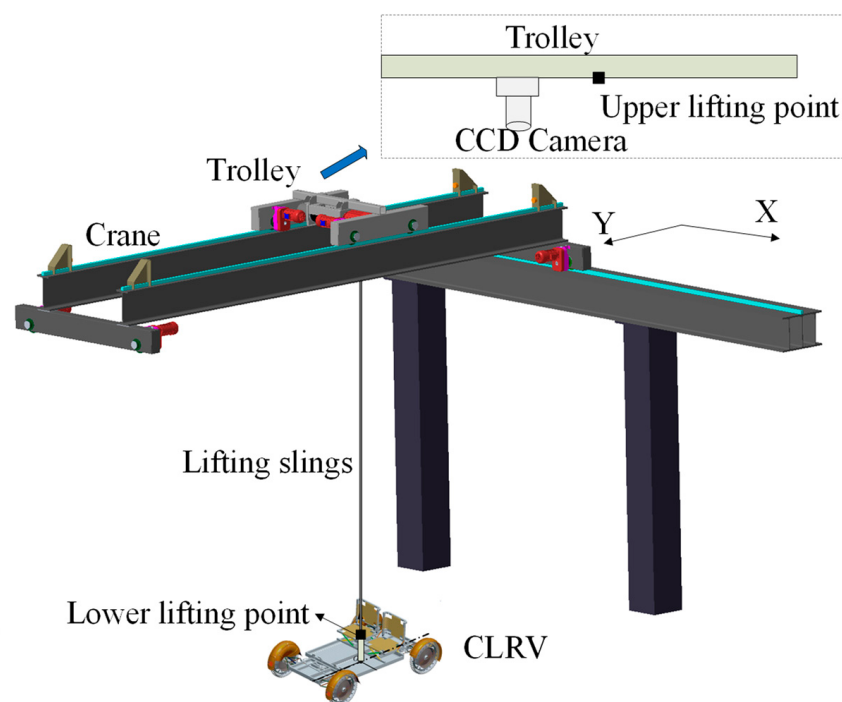


Figure 1. The structure diagram of LGCF.

Overall, this study provides an innovative and promising design proposal for a track-following servo subsystem of an LGCS suitable for the CLRV ground test. The vector control of the PMSM based on SVPWM is used in this paper to achieve a fast response of the track-following servo control. Notably, this paper adopts an EMPC in the position servo closed-loop to obtain good control performance. The EMPC controller can be applied to multi-constrained systems, ensuring a fast response while reducing overshoot. Finally, simulation models of the subsystem are built, and the simulation results are presented and discussed to evaluate the proposed system design and control scheme. The study provides a significant contribution to the field of the LGCS and serves as a valuable reference for future research.

The paper is organized as follows. Section 2 presents the design scheme of the tracking servo subsystem and establishes the system's three-loop servo control model of the current loop, speed loop, and position loop. Section 3 introduces the implementation process of the EMPC control strategy. In Section 4, the desired trajectory of the system, EMPC, and LQI position loop control model parameters are presented. Section 5 discusses and presents the simulation results to evaluate the system performance. Finally, Section 6 concludes the paper.

2. Methodology

In this section, we present the mechanical design of the track-following servo subsystem. The subsystem comprises a moving crane system, a moving trolley system, and multiple motors that enable the track-following servo in both the X and Y directions, as illustrated in Figure 2. The crane is driven by four motors, and the trolley is driven by two motors. The motors power the steel wheels of the crane and trolley to move on the rail. The servo motors transmit power to the system, which is then transmitted to the low-speed shaft end of the reducer via the coupling. The reducer's low-speed shaft end outputs to the driving wheel shaft through another coupling, and the driving wheels propel the crane and trolley to follow the CLRV with high precision.

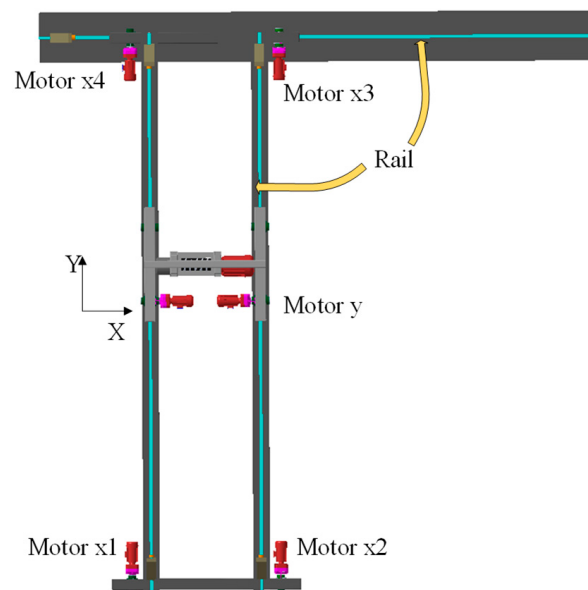


Figure 2. Schematic diagram of the subsystem movement.

Then, based on the mechanical design of the subsystem, suitable equipment is selected, and a simulation model of the track-following servo subsystem is established. In this paper, the servo motors used are PMSMs. The track-following servo subsystem comprises a position servo closed-loop and closed-loop control of the motor speed and current; the crane control model is illustrated in Figure 3. The position control loop is situated on the outer layer of the double closed-loop, which includes the speed and current loops of the servo motor. The position control loop receives a reference signal and subsystem state variables and calculates the expected velocity increment of the crane or trolley in a given unit of time. This value is then passed to the motor's speed loop controller. The speed loop controller calculates the expected current output by comparing the expected speed with the actual speed. The motor's current loop controller then calculates the expected voltage input based on the expected current and the actual current. Together, these three loops form the track-following servo subsystem.

To achieve high-precision control of the crane and trolley, the PMSM vector control method based on SVPWM is adopted for fast response in speed control. The PI control method, with its advantages of being a simple algorithm, having good stability, and having high reliability in the motor speed control system, is widely used for controlling motor speed and current. Therefore, the PI method is applied to the PMSM vector control system, as depicted in Figure 3.

The performance of the outermost position servo loop plays a crucial role in the track-following servo subsystem's tracking performance. However, the position loop's control is limited by the electromechanical system's kinematics and dynamics. To overcome this multi-parameter constraint, the present paper proposes utilizing the EMPC controller within the position servo closed-loop.

where the gross load hauled by the crane is about $m_x = 12,000$ kg, and the gross load hauled by the trolley is about $m_y = 2000$ kg. The number of motors for the moving crane system and the moving trolley system are $q_{motor}^X = 4$ and $q_{motor}^Y = 2$, respectively. The coefficient of rolling friction with railroad steel wheels on steel rails is $\mu = 0.05$, and the radius of the steel wheel is $r_w = 0.2$ m.

The design speed of the crane is larger than the maximum speed (v_{rmax}) of the CLRV, so $v_{ux}^{max} = 5$ m/s is set. Additionally, the VLRV moves in a small range in the Y direction, so $v_{uy}^{max} = 3.5$ m/s is set. The v_{ux} and v_{uy} are the actual speeds of the crane and trolley, respectively.

According to Equation (4), the max speeds of motors n_x^{max} and n_y^{max} can be calculated:

$$n = \frac{60r_g}{2\pi r_w} v_u \quad (4)$$

where the gear ratio of the crane motors is $r_g^X = 10$ and the gear ratio of the trolley motors is $r_g^Y = 10$.

According to the calculation, the motors are selected. The parameters of the motors are shown in the following Table 1.

Table 1. Permanent-magnet synchronous motors parameters table.

Parameters	Motors x (1, 2, 3, 4)	Motors y (1, 2)
bus voltage U_{dc}	380 V	380 V
stator rated current I_N	63 A	20 A
stator inductance $L_d = L_q$	0.0083 H	0.0024 H
stator resistance R	0.376 Ω	0.369 Ω
permanent magnet flux ψ_f	0.9720 Wb	0.8815 Wb
the rotor moment of inertia J	0.2026 kg·m ²	0.0182 kg·m ²
the number of pole pairs P_n	1	1
viscous damping B_u	0.00464 N·m·(s·rad ⁻¹)	0.003 N·m·(s·rad ⁻¹)
the rated speed n	2500 rpm	2500 rpm
The rated torque T_e	123 N·m	37.4 N·m

In the system, the motors' speeds are n_x and n_y , and the actual angular velocities of the motors are ω_{mx} and ω_{my} , respectively.

$$v_{ux} = \frac{2\pi r_w n_x}{60 r_g^X} = \frac{r_w \omega_m^X}{r_g^X} \quad (5)$$

$$v_{uy} = \frac{2\pi r_w n_y}{60 r_g^Y} = \frac{r_w \omega_m^Y}{r_g^Y} \quad (6)$$

In this paper, the PI control is adopted in the motor's current loop and speed loop control. The primary constraints during the controller design are the voltage and current constraints on the quadrature axis and direct axis. The constraints are as follows:

$$\begin{aligned} \sqrt{(i_d^2 + i_q^2)} &\leq \sqrt{2} I_N \\ \sqrt{(u_d^2 + u_q^2)} &\leq \frac{U_{dc}}{\sqrt{3}} \end{aligned} \quad (7)$$

As this is a real physical system, constraints on the states and inputs have to be considered during the controller design given. In the wheel/rail transmission, the premise for obtaining different traction forces is not to destroy the adhesion moment between the wheel/rail. In this paper, the calculation formula of the train wheel/rail adhesion coefficient

u_j is used to calculate the maximum traction torque. When the train speed $v < 50$ km/h, the u_j is as follows [26]:

$$\mu_j = 0.24 + \frac{12}{100 + 8v_{max}} \quad (8)$$

Then, the maximum traction torque is

$$T_j = \frac{\mu_j m g r_w}{r_g q_{motor}} \quad (9)$$

The maximum accelerations a_{ux}^{max} and a_{uy}^{max} can be calculated from the maximum output torque T_{out}^{max} :

$$T_{out}^{max} = \min\{\text{rated torque } T_e, \text{ maximum traction torque } T_j\} \quad (10)$$

The maximum accelerations of the crane and trolley are $a_{ux}^{max} = 1.558 \text{ m/s}^2$ and $a_{uy}^{max} = 2.608 \text{ m/s}^2$, respectively.

Additionally, this system adopts 17-bit incremental rotary encoders to measure the angular velocity and rotor-position of the motors. The measurement error of the motor rotor-position is $\pm 0.001^\circ$, and the measurement error of the motor angular velocity is $\pm 0.2 \text{ rad/s}$. Rotor-position measurement noise adds Gaussian white noise to the θ_e , the amplitude is 0.001° , and the sampling period is $1/10,000 \text{ s}$. Angular velocity measurement noise adds Gaussian white noise to the angular velocity feedback ω_m , the amplitude is 0.2 rad/s , and the sampling period is $1/10,000 \text{ s}$. The current measurement noise also adds Gaussian white noise to the feedback loop of i_d and i_q , the noise amplitude is 0.2 A , and the sampling period is $1/10,000 \text{ s}$. The discrete signals θ_e , i_d , and i_q are delayed by one sampling period. Then, the signals are passed to the PI controllers or $dq/\alpha\beta$ converters.

2.2. Position Servo Loop Model

In this paper, the position servo loop receives the lifting points' information from the position and orientation measurement system. The EMPC controller outputs the desired movement increment Δv_{ux} of the crane in the X direction and the desired movement increment Δv_{uy} of the trolley in the Y direction. In this section, the subscript C denotes the crane and the subscript T denotes the trolley.

Under the fixed coordinates OXY on the ground, the kinematic equation of the trolley and crane in X and Y directions is as follows:

$$u(k) = \begin{pmatrix} \dot{X}_u(k) \\ \dot{Y}_u(k) \end{pmatrix} = \begin{pmatrix} v_{ux}(k) \\ v_{uy}(k) \end{pmatrix} \quad (11)$$

where X_u and Y_u are the position of the crane and trolley in the coordinate system OXY, respectively.

In Figure 3, n_{xref} (rpm) is the reference speed of the motor that drives the crane to move in the X direction, and n_{yref} (rpm) is the reference speed of the motor that drives the trolley to move in the Y direction. The relationship between n_{ref} and $u(k)$ is as follows:

$$n_{ref}(k+1) = \begin{pmatrix} n_{xref}(k+1) \\ n_{yref}(k+1) \end{pmatrix} = \begin{pmatrix} \frac{60r_{gx}}{2\pi r_w} v_{ux}(k) \\ \frac{60r_{gy}}{2\pi r_w} v_{uy}(k) \end{pmatrix} \quad (12)$$

When designing the position loop servo controller, the position servos of the X and Y directions are designed independently. In engineering, the system control generally adopts the incremental control method, and the incremental control is to output the increment Δv of the control variable v every period:

$$v_{ux}(k) = v_{ux}(k-1) + \Delta v_{ux}(k) = v_{ux}(k-1) + u_C(k)T_s \quad (13)$$

$$v_{uy}(k) = v_{uy}(k-1) + \Delta v_{uy}(k) = v_{ux}(k-1) + u_T(k)T_s \quad (14)$$

The reference signal can be regarded as a state variable:

$$X_u(k+1) = X_u(k) + v_{ux}(k)T_s \quad (15)$$

$$Y_u(k+1) = Y_u(k) + v_{uy}(k)T_s \quad (16)$$

The state-space models for the moving crane system and the moving trolley system are as follows:

$$\begin{aligned} x_C(k+1) &= A_C x_C(k) + B_C u_C(k) \\ y_C(k) &= C x_C(k) \end{aligned} \quad (17)$$

$$\begin{aligned} x_T(k+1) &= A x_T(k) + B u_T(k) \\ y_T(k) &= C_T x_T(k) \end{aligned} \quad (18)$$

where

$$\begin{aligned} \begin{bmatrix} -40 \\ -5 \end{bmatrix} &\leq x_C(k) = \begin{bmatrix} X_u(k) \\ v_{ux}(k-1) \end{bmatrix} \leq \begin{bmatrix} 40 \\ 5 \end{bmatrix} \\ \begin{bmatrix} -10 \\ -3.5 \end{bmatrix} &\leq x_T(k) = \begin{bmatrix} Y_u(k) \\ v_{uy}(k-1) \end{bmatrix} \leq \begin{bmatrix} 10 \\ 3.5 \end{bmatrix} \\ \begin{bmatrix} -1.558 \\ -2.608 \end{bmatrix} &\leq \begin{pmatrix} u_C(k) \\ u_T(k) \end{pmatrix} \leq \begin{bmatrix} 1.558 \\ 2.608 \end{bmatrix} \\ A_C = A_T &= \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix}, \quad B_C = B_T = \begin{bmatrix} T_s^2 \\ T_s \end{bmatrix}, \\ C_C = C_T &= [1 \quad 0]. \end{aligned}$$

The deviation in the crane and trolley's position in the X and Y directions from the desired trajectory converges to zero through the proposed control scheme. To implement Equations (17) and (18) in an explicit MPC scheme, a zero-order hold method with a sampling time of 0.005 s is utilized in this paper.

3. Explicit Model Predictive Control

To ensure robustness and meet complex constraints, this study employs MPC [27,28] as a crucial optimal control scheme. At each sampling time k , the optimal control law of the inner loop is solved by formulating and solving a control problem that is then transformed into an online quadratic programming (QP) problem. The cost function used in this control problem is defined as follows:

$$\begin{aligned}
\min_{\Delta u} \left\{ J(U, x(k)) = & x_{k+N_p|k}^T P x_{k+N_p|k} \right. \\
& + \sum_{i=0}^{N_p-1} [(y_{k+i|k} - y_{k+i|k}^{ref})^T Q_y (y_{k+i|k} - y_{k+i|k}^{ref}) + x_{k+i|k}^T Q x_{k+i|k} \\
& \left. + u_{k+i|k}^T R u_{k+i|k}] \right\} \\
\text{s.t. } & x_{k|k} = x(k) \\
& x_{k+i+1|k} = A_d x_{k+i|k} + B_d u_{k+i|k} \\
& y_{k+i|k} = C_d x_{k+i|k} \\
& u_{min} \leq u_{k+i|k} \leq u_{max}, i = 0, 1, \dots, N_c \\
& x_{min} \leq x_{k+i|k} \leq x_{max}, i = 0, 1, \dots, N_p \\
& u_{k+i|k} = K x_{k+i|k}, N_c < i \leq N_p
\end{aligned} \tag{19}$$

where A_d , B_d , and C_d are the discrete-time versions of the system, input, and output matrices, respectively. N_p is the prediction horizon and N_c is the control horizon. The notation $x_{k+i|k}$ represents the predicted value of x at i steps ahead of k . Here, Q , R , and P are the weighting matrices for the state, input, and terminal state, respectively. Q_y is the output weighting matrix used to measure tracking error.

In addition, the output can be obtained with corresponding dimensions K and P by solving the discrete-time algebraic Riccati equation [29], given by

$$\begin{aligned}
P &= A_d^T P A_d - (A_d^T P B_d) (R + B_d^T P B_d)^{-1} (B_d^T P A_d) + Q \\
K &= (R + B_d^T P B_d)^{-1} B_d^T P A_d
\end{aligned} \tag{20}$$

Using these weighting matrices, the MPC controller computes a sequence of optimal vectors U that minimize the cost function J .

Although MPC offers several advantages, such as optimal control and handling of constraints, the online optimization process can lead to a significant computational burden, which is a major drawback. To address this issue, Alberto proposed a new MPC scheme that can reduce the computational load [30].

The equations for predicting the state vector $X(k)$ can be obtained through the following derivation:

$$X(k) = \Theta x(k) + \Lambda U(k) \tag{21}$$

where

$$\begin{aligned}
X(k) &= \begin{bmatrix} x(k+1|k) \\ \vdots \\ x(k+N_p|k) \end{bmatrix}, U(k) = \begin{bmatrix} u(k|k) \\ \vdots \\ u(k+N_p-1|k) \end{bmatrix}, \\
\Theta &= \begin{bmatrix} A_d \\ A_d^2 \\ \vdots \\ A_d^{N_p} \end{bmatrix}, \Lambda = \begin{bmatrix} B_d & 0 & 0 & \dots & 0 \\ A_d B_d & B_d & 0 & \dots & 0 \\ A_d^2 B_d & A_d B_d & B_d & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_d^{N_p-1} B_d & A_d^{N_p-2} B_d & A_d^{N_p-3} B_d & \dots & B_d \end{bmatrix}.
\end{aligned}$$

Equations (19) and (21) can be reformulated as follows:

$$\begin{aligned}
V(x(k)) &= U(k)^T (\Lambda^T Q_{N_p} \Lambda + R_{N_c}) U(k) + 2x(k)^T \Theta^T Q_{N_p} \Lambda U(k) \\
&\quad + x(k)^T (\Theta^T Q_{N_p} \Theta + Q) x(k)
\end{aligned} \tag{22}$$

where

$$\hat{Q} = \begin{bmatrix} Q & & \\ & \ddots & \\ & & Q \\ & & & P \end{bmatrix}, \hat{R} = \begin{bmatrix} R & & \\ & \ddots & \\ & & R \end{bmatrix}.$$

By defining $H = (\Lambda^T \hat{Q} \Lambda + \hat{R})$, $F = \Theta^T \hat{Q} \Lambda$, and $G = \Theta^T Q_{N_p} \Theta + Q$, Equation (22) can be formulated as the following equivalent form:

$$\begin{aligned} V(x(k)) &= \frac{1}{2} U(k)^T H U(k) + x(k)^T F U(k) \\ \text{s.t. } \hat{A} U(k) &\leq W + E x(k) \end{aligned} \quad (23)$$

where

$$\hat{A} = \begin{bmatrix} \Lambda_i \\ -\Lambda_i \end{bmatrix}, i = 1, \dots, N_p, W = \begin{bmatrix} x_{max} \\ -x_{min} \end{bmatrix}, E = \begin{bmatrix} -A_d^i \\ A_d^i \end{bmatrix}, i = 1, \dots, N_p.$$

In Equation (23), Λ_i indicates the i th row of Λ .

By defining $z \triangleq U(k) + H^{-1} F^T x(k)$, the reformulated optimization problem presented in Equation (23) can be expressed as a mixed-integer quadratic programming (mp-QP) problem, as shown below [24]:

$$\begin{aligned} V_z(x) &= \min_z \frac{1}{2} z^T H z \\ \text{s.t. } \hat{A} z &\leq W + S x(k) \end{aligned} \quad (24)$$

where $S \triangleq E + \hat{A} H^{-1} F^T$ and $V_z(x) = V(x(k)) - \frac{1}{2} x(k)^T (G - F H^{-1} F^T) x(k)$.

The Karush–Kuhn–Tucker (KKT) optimization conditions are used for the above problem [30]:

$$\begin{aligned} H z + \hat{A}^T \lambda &= 0, \lambda \in \mathbb{R}^q \\ \lambda^i (\hat{A}^i z - W^i - S^i x) &= 0, i = 1, \dots, q \\ \lambda &\geq 0 \\ \hat{A} z &\leq W + S x \end{aligned} \quad (25)$$

Solving the above equations:

$$\lambda_a = -(\hat{A}_a H^{-1} \hat{A}_a^T)^{-1} (W_a + S_a x) \quad (26)$$

$$z = H^{-1} \hat{A}_a^T (\hat{A}_a H^{-1} \hat{A}_a^T)^{-1} (W_a + S_a x) \quad (27)$$

Based on the above equation, it can be observed that Equations (26) and (27) are linear affine functions of the state $x(k)$. Furthermore, it is apparent that the control variable U is also a linear affine function of the state $x(k)$ when considered in conjunction with equation $z = U + H^{-1} F^T x(0)$. The subscript a indicates the active constraint, and the subscript i indicates the inactive constraint.

Based on the KKT condition, it is evident that the validity of the above equation is contingent on satisfying the inequality constraints:

$$-(\hat{A}_a H^{-1} \hat{A}_a^T)^{-1} (W_a + S_a x(0)) \geq 0 \quad (28)$$

$$\hat{A} H^{-1} \hat{A}_a^T (\hat{A}_a H^{-1} \hat{A}_a^T)^{-1} (W_a + S_a x(0)) \leq W + S x(0) \quad (29)$$

The polyhedral set (critical region) CR_0 can be formed:

$$CR_0 = \{x \in \mathbb{R}^n | \lambda_a \geq 0, \hat{A}_i z \leq W_i + S_i x\} \quad (30)$$

By applying different constraints, more critical regions are formed for different groups of states. Therefore, a map of states to optimal control inputs is eventually created.

4. Controller Design

4.1. Desired Path

First, the reference signal needs to be determined. In this system, the input signal should be given according to the driving characteristics of the CLRV. The performance test of the LVR should include the ability to accelerate, decelerate, drive at a uniform speed, move forward, reverse, turn, and climb over slopes of about 20° . Suppose the maximum speed of the pre-researched CLRV is $v_{rmax} = 4 \text{ m/s}$ with $a_{rmax} = 1 \text{ m/s}^2$.

Additionally, the signal-to-noise ratio of a_{rx} and a_{ry} is 20 dB. After integrating the accelerations a_{rx} and a_{ry} , the speeds v_{rx} and v_{ry} can be obtained. Then, integrating the speeds v_{rx} and v_{ry} , the position information X_r and Y_r of the CLRV can be obtained, respectively. Figure 4 illustrates the position X_r as well as the speed v_{rx} of path one of the CLRV in the X direction. When the CLRV is going uphill or downhill, its speed in the X direction quickly decreases before stabilizing as it ascends, and quickly increases before stabilizing as it descends.

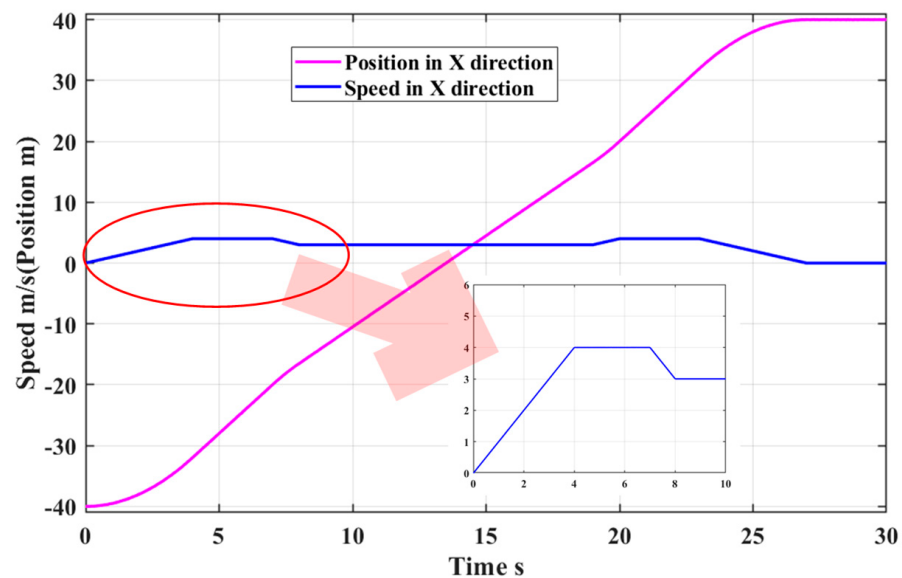


Figure 4. Desired path one for track-following servo control is plotted in this figure. The initial position of the CLRV is $(-40, 0)$. Path one is the trajectory of the CLRV moving in the X-direction. The trajectory consists of uniform acceleration, uniform deceleration, uniform motion, and changes in X-directional speed due to uphill and downhill slopes.

Path two is the trajectory of the CLRV moving forward and backward in the Y-direction. The speed v_{ry} and position Y_r changes in the Y direction of path two are shown in Figure 5.

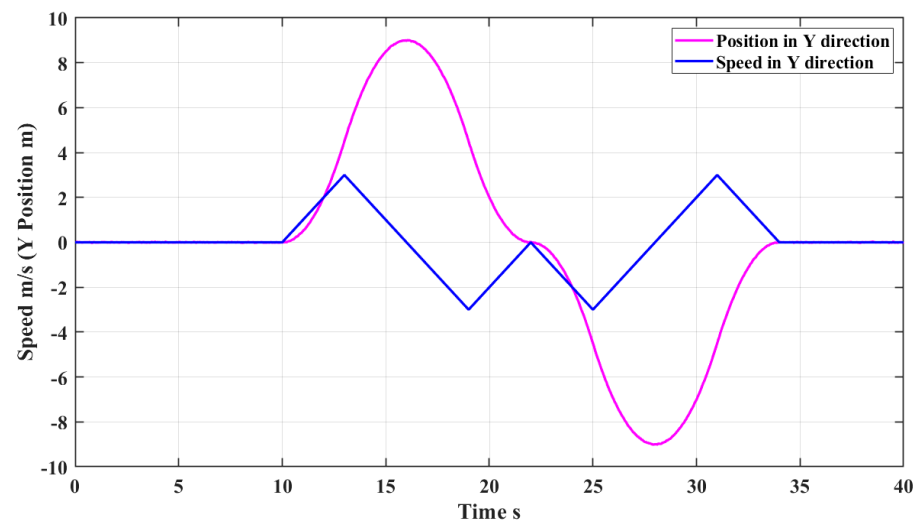


Figure 5. Desired path two for track-following servo control is plotted in this figure. The initial position of the CLRV is $(-40, 0)$.

Path three represents the trajectory of the CLRV as it makes a turn with a radius of 10 m and a velocity of 3 m/s. Path four is the trajectory of the CLRV navigating a turn while avoiding obstacles. The speeds of the CLRV in the X and Y directions for paths three and four are also displayed in Figures 6 and 7, respectively.

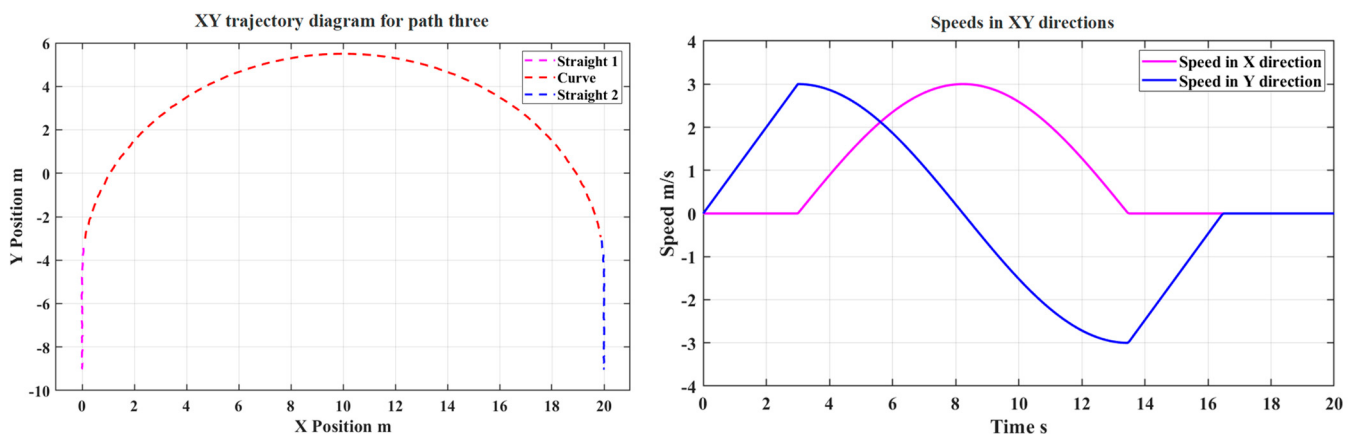


Figure 6. CLRV's motion trajectory and speeds in the XY directions for desired path three. The initial position of the CLRV is $(0, -9)$. This path mainly consists of three parts: a section of straight motion with uniform acceleration, a turning curve with a radius of 10 m, and a section of straight motion with uniform deceleration.

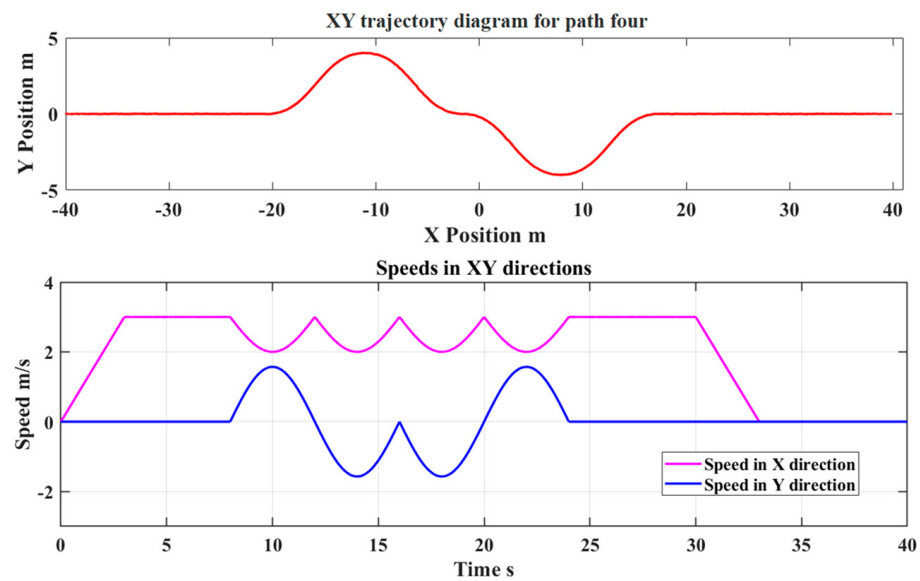


Figure 7. CLRV's motion trajectory and speeds in the XY directions for desired path four. The initial position of the CLRV is $(-40, 0)$. This path mainly comprises five parts: a uniformly accelerated straight motion part, two turning curves, uniform straight motions, and a uniformly decelerated straight motion part.

In order to accurately control the crane, the controller must handle digital values obtained from sensors rather than continuous values of the states. Therefore, it is necessary to convert the desired path signal from continuous time to discrete time for more accurate representation. This system uses a monocular vision system to measure the position and orientation of lifting points, with a range of $-40 \leq X \leq 40$ m (or $-10 \leq Y \leq 10$ m) and positioning accuracy of ± 10 mm. The processing frequency of the visual system is 20 Hz. The present positions of the crane and the trolley in the X and Y directions are measured by the high-precision magnetic scale, the response time is 1 ms, and the measurement error is better than ± 10 μ m.

The position measurement noise is added to the output of the desired path with Gaussian white noise. The Gaussian noise amplitude is 0.01 m and the sampling time is 0.05 s. The sampling period of the desired path is 0.05 s, the discrete signal is delayed by one sampling period, and then the signal is passed to the position servo loop controller.

4.2. Design of Explicit MPC Controllers

This section elaborates on the design of the explicit model predictive controller, including the controller structure and the process of determining the weighting matrices Q , R , and Q_y , are shown in the following Table 2. In this section and the next section, the superscript C refers to the crane and the superscript T refers to the trolley.

Table 2. EMPC Controller design parameters.

Parameters	Value
Predicted horizon N_p	$N_p^C = 12, N_p^T = 6$
Control horizon N_c	$N_c^C = N_c^T = 2$
State weighting matrix Q	$Q^C = Q^T = \begin{bmatrix} 0.00001 & 0 \\ 0 & 0.00001 \end{bmatrix}$
Output weighting matrix Q_y	$Q_y^C = Q_y^T = 10,000$
Input weighting matrix R	$R^C = R^T = 0.08$
Sampling time T_s	5 ms

In this paper, the EMPC controller, designed using the MPT toolbox 3.0 [31], generates an optimal input while satisfying the system's constraints. The performance of the EMPC

scheme can be tuned by appropriately adjusting the weighting matrices Q , R , and Q_y , and by a suitable choice of the prediction horizon N_p and N_c . The EMPC controller for the crane moving system has 993 critical regions, whereas the EMPC controller for the trolley moving system has 685 critical regions. Figure 8 shows the feasible critical regions of the trolley moving system's controller.

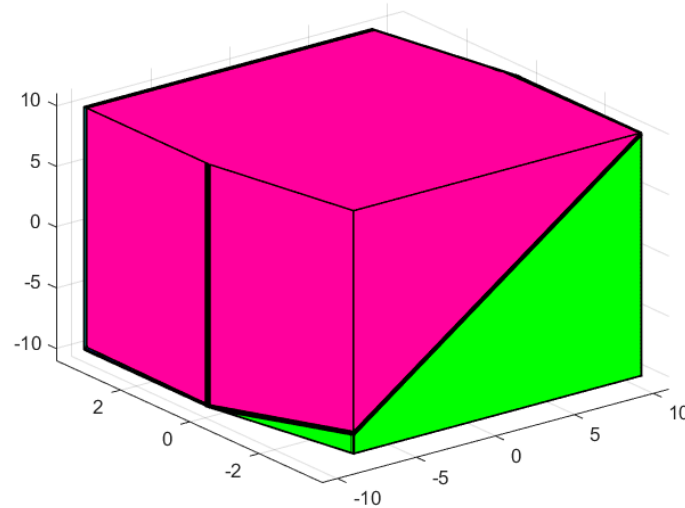


Figure 8. Critical regions. The figure illustrates the critical regions generated by the EMPC controller for the moving trolley system.

4.3. Linear-Quadratic-Integral Controller Design

In this paper, the LQI controller [32] is also employed for the position-loop servo control and is compared with the performance of the EMPC controller. Taking crane control as an example, in the design of the LQI controller, the ultimate goal is to track the position reference of the lunar rover. Therefore, in practice, the optimal control scheme should be applied as follows:

$$u_c^{LQI} = -K_{LQI}^C \begin{bmatrix} x \\ x_i \end{bmatrix} = -K_{LQI}^C \begin{bmatrix} e_X(k) \\ v_{ux}(k-1) \\ \int e_X(k) \end{bmatrix} \quad (31)$$

where $e_X(k) = X_r(k) - X_u(k)$ is the tracking error. Assuming that the reference signal is constant in the future, the state equation for the reference signal is:

$$X_r(k+1) = X_r(k) \quad (32)$$

Combining Equations (31), (32), and (17) results in the following equation:

$$\begin{bmatrix} e_X(k+1) \\ v_{ux}(k) \\ \int e_X(k+1) \end{bmatrix} = \begin{bmatrix} 1 & -T_s & 0 \\ 0 & 1 & 0 \\ 1 & -T_s & 1 \end{bmatrix} \begin{bmatrix} e_X(k) \\ v_{ux}(k-1) \\ \int e_X(k) \end{bmatrix} + \begin{bmatrix} -T_s^2 \\ T_s \\ -T_s^2 \end{bmatrix} u_c(k) \quad (33)$$

Similarly, we can obtain the spatial state equation for position tracking control of the trolley by following the same procedure as we did for the crane moving system. In both the crane and trolley moving systems for position servo control, the weighting matrices used in the LQI controllers are as follows:

$$Q_{LQI}^C = \begin{bmatrix} 40,000 & & \\ & 0.00001 & \\ & & 1 \end{bmatrix}, \quad Q_{LQI}^T = \begin{bmatrix} 10,000 & & \\ & 0.00001 & \\ & & 1 \end{bmatrix}, \quad (34)$$

$$R_{LQI}^C = R_{LQI}^T = 0.1,$$

During the parameter selection process of the weight matrix, special consideration is given to prioritize accurate tracking. As a result, the error state is given a high penalty. Additionally, the integral error state is also assigned a high penalty to minimize the deviation from the steady state as much as possible. Furthermore, the plant input weight is chosen relatively high to prevent any significant changes in the system. Then, the state feedback gain K_{LQI} for the LQI controllers can be determined by solving the algebraic Riccati equation, as illustrated in Equation (20).

5. Results and Discussion

In this system, the impact of the tracking error of the track-following system mainly includes the impact on the drawbar pull force F_{DP} [33] and gravity compensation force F_C of the CLRV.

Supposing that the upper lifting point is positioned 10 m above the CLRV, the drawbar pull force error in the horizontal direction caused by the tracking error denoted as ΔF_h can be expressed as:

$$\frac{\Delta F_h}{\frac{5}{6}G_c} = \frac{\delta P}{10} \quad (35)$$

where G_c is the weight of the CLRV and δP is the tracking error.

The gravity compensation force error ΔF_v in the vertical direction caused by the position tracking error is:

$$\Delta F_v = F_C \left[1 - \cos \left(\arctan \frac{\delta P}{10} \right) \right] \quad (36)$$

Supposing that the drawbar pull factor of the CLRV's wheel with a radius of 0.4 m on loose soil is $u_{DP} = 0.8$, the maximum drawbar pull force and gravity compensation force can be roughly expressed as:

$$F_{DP} = u_{DP} W_N \quad (37)$$

$$F_C = \frac{5G_c}{6} \quad (38)$$

where W_N is the wheel vertical load. Hence, the maximum drawbar pull of the entire rover can be estimated by setting W_N as $1/6G_c$.

Combining Equations (35)–(38) gives:

$$\varepsilon_h = \frac{\Delta F_h}{F_{DP}} \quad (39)$$

$$\varepsilon_v = \frac{\Delta F_v}{F_C} \quad (40)$$

where ε_h and ε_v are the error impact factors to measure the influence of tracking errors.

This section presents and discusses the simulation results of the track-following servo control for paths one, two, three, and four using the PI, LQI, and EMPC controllers.

Figure 9 presents a comparison of simulation results for track-following servo control along path one, using three different controllers: PI, LQI, and EMPC. The “Reference” curve shows the real-time position of the CLRV. The figure displays the tracking results, tracking errors, and the crane speed of the track-following servo for each controller.

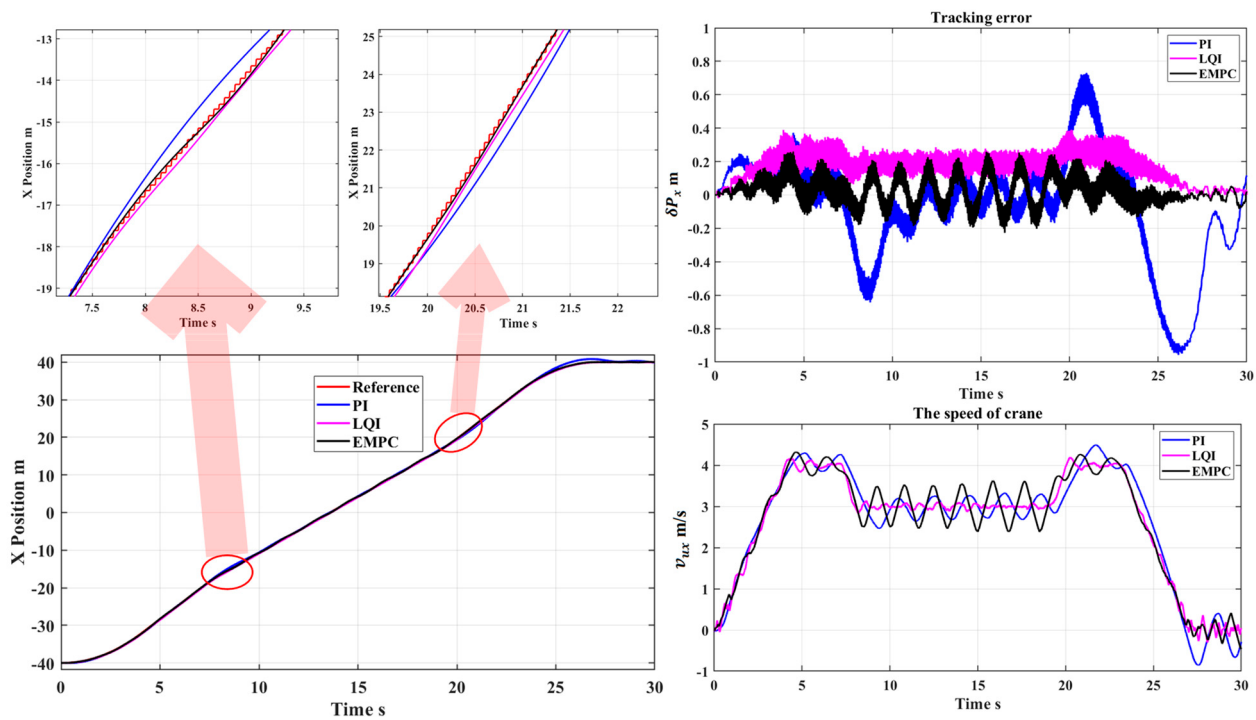


Figure 9. The simulation results' comparison of tracking path one used the PI, LQI, and EMPC controllers. The figures present the following results: the results of the crane tracking desired path one in the X direction; tracking errors δP_x between the crane's position and the desired position along path one in the X direction; the crane speed v_{ux} of tracking path one.

It can be observed from Figure 9 that the EMPC controller has the best performance and the smallest tracking error against the disturbance caused by the rapid change in the X-direction speed of the CLRV, followed by the LQI and PI controllers. Moreover, by examining the motion speed diagram of the crane, it can be inferred that the tracking stability of LQI is highest.

As shown in Figure 9, the positional deviation resulting from the track-following servo of the PI controller is significantly greater than those of the EMPC and LQI controllers. This is primarily due to the high inertia of the crane, which poses challenges in tracking the desired path. To overcome this, a simple PI controller with higher proportional coefficients is employed, leading to improved response speed but degraded steady-state performance. Interestingly, LQI has a lower settling time than PI and EMPC, and its stability is best. This can be attributed to its very high weight in the state of the tracking error, which helps it reach the steady state earlier. However, LQI suffers from delay errors between the desired path and the crane position, resulting from its reliance on the output value of the error integrator.

In contrast, the EMPC controller enhances control performance by generating optimal inputs while satisfying constraints. The model predictive control algorithms used in EMPC are more complex, taking into account various parameters and predicting the most optimal path for possible trajectories. As a result, the EMPC controller performs better at minimizing errors compared to controllers that use a simple cost function or a set of gains to correct deviations.

Figure 9 shows the tracking error of tracking desired path one using the EMPC controller. P_x refers to the real-time error of the crane and lunar rover in the X direction, while P_y refers to the real-time error of the trolley and lunar rover in the Y direction. In the tracking servo of path one, there is only an error in the X direction. The tracking error $\delta P = \delta P_x$ and the tracking error of the EMPC controller for path one is within 0.2 m.

Figure 10 depicts the simulation results of the trolley tracking path two, which involves frequent acceleration, deceleration, and forward and reverse movements in the Y direction.

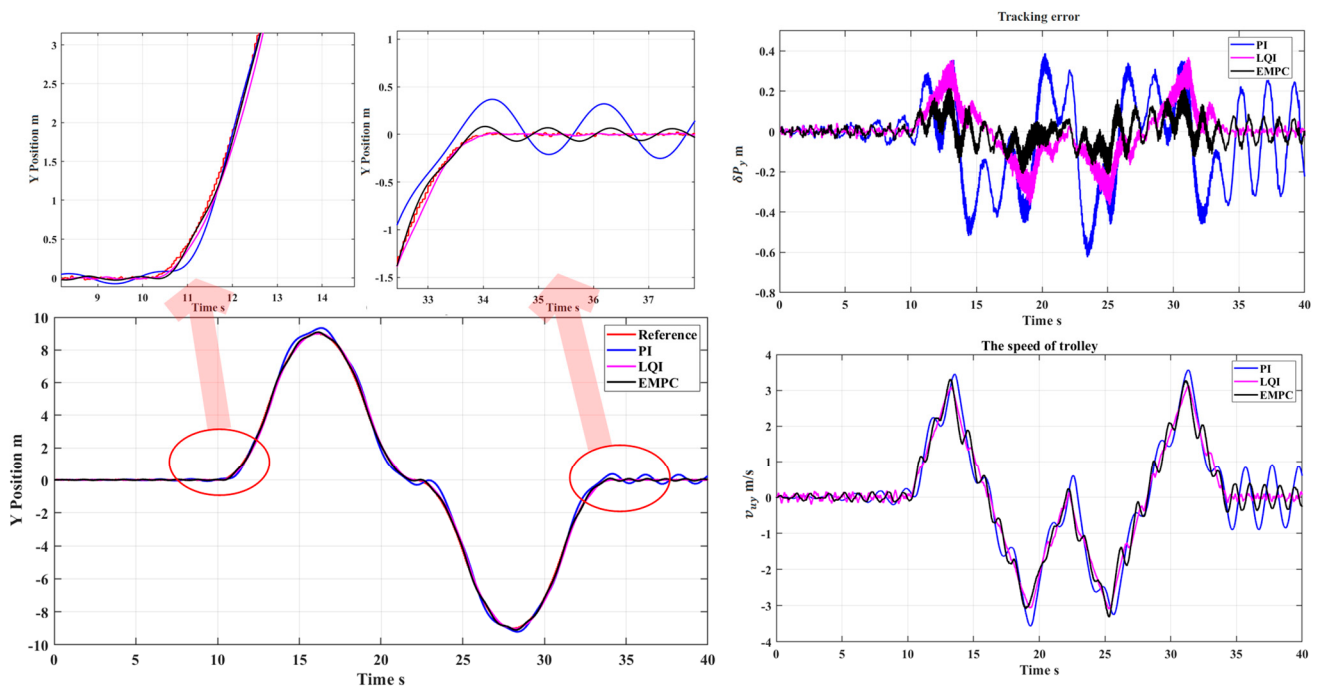


Figure 10. Results of the trolley tracking desired path two. The figures present the following results: the results of trolley tracking desired path one in the Y direction; tracking errors δP_y between the trolley's position and the desired position along path two in the Y direction; the trolley speed v_{uy} of tracking path two.

Figure 10 shows the simulation results of the trolley tracking path two in the Y direction. The tracking error is mainly caused by the trolley's inertia. Comparing it with Figure 9, it can be observed that as the crane's inertia is much greater than that of the trolley, the error will be even greater when the crane tracks the expected path with rapid changes in the X-directional speed. The results shown in Figure 10 show the trolley's speed v_{uy} of tracking path two. From the tracking error plot and trolley speed plot, it can be seen that large errors usually occur during the time periods when the trolley undergoes acceleration and deceleration switching. To minimize the impact of the crane's large inertia on tracking performance, it is recommended to avoid frequent acceleration and deceleration of the lunar rover in the X direction. Instead, it is advisable to conduct forward and reverse movement performance testing solely in the Y direction to achieve optimal results.

In the tracking servo of path two, there is only an error in the Y direction. The tracking error $\delta P = \delta P_y$ and the tracking error of the EMPC controller for path two is within 0.2 m.

Figure 11 depicts the simulation results of the crane and trolley tracking desired path three, which follows a turning motion trajectory of the CLR V with a radius of 10 m, and operates at a speed of 3 m/s. On the other hand, Figure 12 illustrates the crane and trolley tracking path four, which represents the driving trajectory of the CLR V when encountering continuous turns during obstacle avoidance. The CLR V operates at a speed of around 3 m/s while following this path.

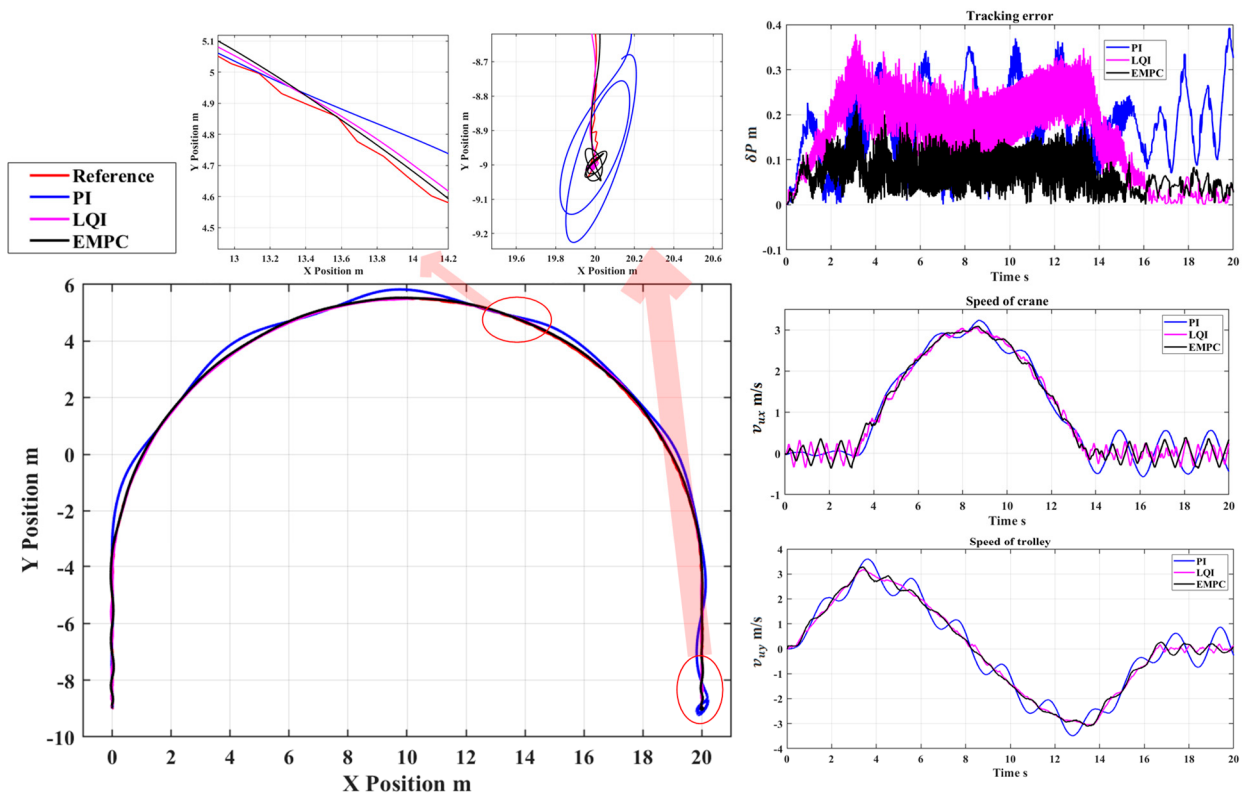


Figure 11. The results of tracking desired path three by the crane and trolley are presented. The figures illustrate the following outcomes: a comparison between the trajectory of the upper lifting point and the expected trajectory under three different controllers, the tracking error $\delta P = \sqrt{\delta P_x^2 + \delta P_y^2}$ of the track-following servo subsystem, and the movement speed of both the crane and trolley.

Figures 11 and 12 illustrate that the EMPC controller results in the smallest tracking error, followed by LQI and PI controllers. Furthermore, the results suggest that the LQI controller exhibits excellent stability, as the movement speed of the crane and trolley remains relatively stable in response to dynamic disturbances. On the other hand, when using a PI controller for a large inertia system, the overshoot can be relatively large, and it can be challenging to balance the response speed and stability.

Figures 11 and 12 displays the simulation results of crane and trolley tracking for desired paths three and four, utilizing the EMPC controller. The tracking error $\delta P = \sqrt{\delta P_x^2 + \delta P_y^2}$ is basically less than 0.2 m.

The simulation results show that the maximum tracking errors δP of the track-following servo subsystem using EMPC controllers are almost less than 0.2 m. According to Equations (39) and (40), it can obtain the influence factor of the tracking error on the CLRV motion in the horizontal direction:

$$\varepsilon_h < 0.125 \quad (41)$$

In addition, the error impact factor in the vertical direction is as follows:

$$\varepsilon_v < 0.00045 \quad (42)$$

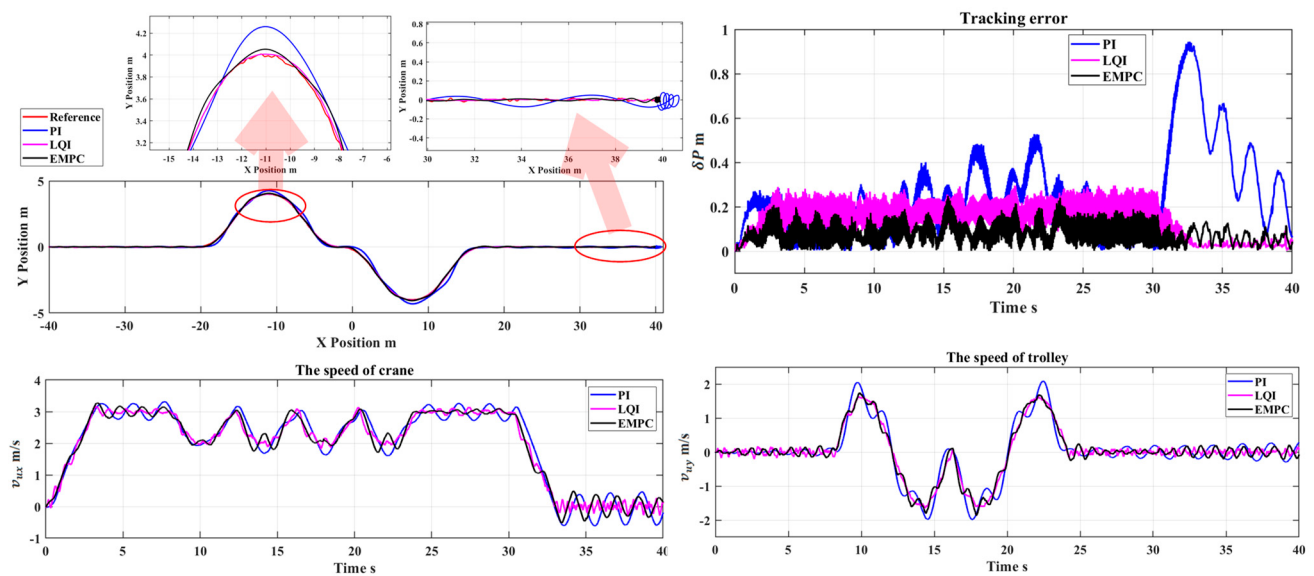


Figure 12. The results of tracking desired path four by the crane and trolley are presented. The figures illustrate the following outcomes: a comparison between the trajectory of the upper lifting point and the expected trajectory under three different controllers, the tracking error $\delta P = \sqrt{\delta P_x^2 + \delta P_y^2}$ of the track-following servo subsystem, and the movement speed of both the crane and trolley.

The simulations yield some key findings: the EMPC demonstrates a notably impressive performance for the system, with explicit MPC delivering the objectively best results. While the PI and LQI controllers show comparatively inferior results, they remain reliable options with their own strengths. The PI controller is easy to apply, while the LQI controller exhibits excellent robustness and stability. However, their application is limited for multi-constraint control systems. Although the EMPC shows good performance under different expected trajectories, it also has some limitations in terms of stability, especially in dealing with large disturbances in the X direction (i.e., when the CLRVR speed changes rapidly). In such cases, the crane may lose control. To address this issue, future work will focus on conducting relevant methods to further analyze the stability of the proposed EMPC controller.

In conclusion, EMPC is a controller that can provide the smallest possible dynamic tracking error and steady-state error under the condition of dealing with multiple constraints, and it has better control performance. Moreover, frequent acceleration and deceleration should be avoided in the X direction when driving the CLRVR, to reduce the impact of the large inertia of the crane on the controller's tracking performance.

Based on the simulation results, we compare the tracking performance of the track-following servo subsystem of the suspension gravity compensation system to that of the system designed by Liu et al. [2]. Although the maximum tracking error of Liu et al.'s system is approximately 0.1 m, its crane employs open-loop control, making it only suitable for tracking a slow-moving unmanned lunar rover. In contrast, the research presented in this paper provides a solution to the theoretical research gap of the track-following servo subsystem suitable for CLRVR experiments.

6. Conclusions

This paper proposes a design and control scheme for a track-following servo subsystem of a LGCS suitable for CLRVR ground testing:

1. The track-following servo subsystem consists of a crane, trolley, and servo motors. The crane moves along the bridge, tracking the real-time position of the CLRVR, while the trolley moves along the crane girder to follow the real-time position of the CLRVR. Three-loop control models are established for both the crane and trolley, including the position loop, motor speed loop, and current loop.

2. The driving force of the track-following servo subsystem is provided by a PMSM. Specific parameters for the motor and transmission mechanism are determined based on the subsystem's motion capability. PMSM vector control based on the SVPWM is adopted to achieve fast response and precise control of the motor speed. PI controllers are employed in both the current and speed loops of the motors.
3. In the position loop control of the track-following servo subsystem, explicit MPC control is introduced for multi-parameter constraint control. This paper presents an EMPC controller suitable for the track-following servo subsystem, including the cost function design and offline calculation process. The weighting matrices, prediction horizon, and control horizon are also determined.

Especially, the effectiveness of the proposed EMPC controller is demonstrated through a comparison with PI and LQI controllers. The simulation results show that the maximum tracking error δP of the track-following servo subsystem is consistently below 0.2 m. The impact of the errors on the drawbar pull is within 12.5%, and their effect on the compensation force is negligible. The simulation results also suggest that, due to the large inertia of the crane, the CLRV should avoid frequent forward, backward, acceleration, and deceleration in the X direction to reduce the influence of the crane's large inertia on tracking performance. These simulation results provide valuable theoretical support for designing a track-following servo subsystem that is suitable for CLRV ground testing.

In our future work, our objective is to develop a track-following servo subsystem that is suitable for ground testing of the CLRV. The primary contribution of this paper is the development of an EMPC controller for the position control loop, along with PMSM vector control, which has demonstrated excellent tracking performance for the subsystem. However, implementing the EMPC controller in engineering settings may pose significant challenges. In our upcoming research, we plan to refine our work further, including addressing potential deviations in motor load torque, exploring cooperative control of multiple motors, and enhancing the robustness of the EMPC controller. These are essential considerations that must be addressed to fully realize the potential of the proposed approach in practical applications.

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