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Conceptualization of Markov Processes in Cyber-Physical Systems: Modelling, Prediction, and Control

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ABSTRACT: Cyber-Physical Systems (CPS) bring together physical processes with computing, communication, and control. They often operate in environments full of uncertainty, noise, and constant change, which makes traditional deterministic models struggle to capture how these systems really behave. This work introduces a more flexible framework based on Markov processes that helps model, predict, and control CPS in a more realistic way. By viewing system behaviour as probabilistic transitions between states, it becomes easier to analyze uncertainty and understand how the system evolves over time. The study looks at discrete-time Markov chains and expands the discussion to Hidden Markov Models (HMMs) and Markov Decision Processes (MDPs), allowing both visible and hidden aspects of system dynamics to be represented. It outlines a well-defined process for defining states, calculating transition probabilities, and making forecasts. The paper explores, in addition to that, the use of control techniques based on the use of probability theory and shows that these methods have a greater level of robustness compared to traditional control techniques. An example is given to show how this model improves performance and flexibility. All in all, Markov modelling is a good starting point for dealing with the challenges in CPSs, paving the way for integration with other tools.

KEYWORDS: Cyber-Physical Systems, Markov Chains, Markov Decision Processes, Stochastic Control, Probabilistic Prediction, System Reliability.

INTRODUCTION

Cyber-Physical Systems (CPS) constitute one of the most important developments in modern engineering as they combine computational, communication, and physical processes into integrated systems characterized by tight coupling and real-time operation. Extremely ubiquitous nowdays across such areas as smart grids, industrial automation, autonomous transport, and networked infrastructure these systems require advanced analysis. The integration of technological systems into the urban environment requires technical precision and strategic planning. The main goal is to achieve environmental and social sustainability (Nikolov, 2024a). Smart city are controlis an excellent example in this direction, serving as a micro-model of sustainable urban development (Nikolov, 2025a). Another critical application is the optimization of energy consumption in the home through IoT and artificial intelligence (Nikolov, 2024b). These systems demonstrate the potential of mathematical modeling for effective resource management (Nikolov, 2024c). Through their implementation, a significant reduction in the ecological footprint in modern smart cities is achieved (Nikolov, 2025b). Similar challenges are also observed in industrial environments, where technological obsolescence affects decisions related to production capacity development and long-term system sustainability (Peneva, 2024).
Based on Alanen et al. (2022), "any assessment of the reliability and risk in such systems necessitates probability-based approaches because of the very nature of uncertainties and complexities associated with them". In addition, traditional deterministic models often prove unable to reflect the stochastic nature of CPS operating in noisy environments with limited access to information and continuous modifications. Kovtun et al., (2022) have shown that Markov chain-based methodologies are quite efficient for assessing functional safety in such systems as their states tend to be influenced by uncertainties. With the increasing levels of autonomy, connectivity, and complexity in the architectures of CPS, the significance of probabilistic approaches tends to grow considerably. Markov processes appear to be the key tools for modelling time-dependent behavior in stochastic systems. According to Gao et al., (2023), Markov models offer quite an efficient basis for analysing CPS exposed to attacks like denial-of-service as well as developing protective control policies. In a similar manner, Zaytseva et al., (2023) have used Markov process methodologies for predicting probabilities of cyber-attacks in maritime CPS. Apart from cyber-security concerns, Markov processes are extensively applied to solving fault detection and system reliability-related problems. Gu et al., (2019) claim that combining fault trees with

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Markov chains improves models of failure propagation in industry systems. Reed & Ziadé (2023) have focused specifically on transitory Markov chain-based analyses of security-related behaviors of CPS.

Another popular approach for coping with situations where system states are only partially observable is based on the use of Hidden Markov Models (HMM). Karageorgiou & Karyotis (2022) highlight the efficiency of stochastic modelling with the help of Markov processes for malware propagation in networked systems due to the impossibility to directly observe their states. Similarly to the previous statement, Gore et al., (2017) claim that Markov chain-based analysis of system states provides rather accurate results when applied to modelling of cyber threats. Markov Decision Processes (MDPs) are also crucial for making decisions in uncertain conditions. Leong et al., (2018) prove the effectiveness of reinforcement learning approaches rooted in MDP theory in terms of scheduling and control of CPS.

A number of studies attempted to explore the application of Markov-based modelling to more recently developed systems such as blockchains and distributed networks. Li et al., (2019) apply Markov processes to analysing the behavior of blockchain networks including their security aspects. Similarly, Santos et al., (2019) focus on assessing vulnerabilities of distributed systems.

Xu et al., (2016) indicate that modelling of cyber defense processes in stochastic terms should imply trade-offs between granularity and computational tractability of the problem. Lanotte et al., (2017) develop probabilistic modelling approaches for CPS but also highlight their scalability limitations. Based on the above body of literature, the current research project focuses on developing a framework for the use of Markov processes in the modelling, prediction, and control of CPS.

Mathematical Modelling Framework and Control Strategies in CPS

To describe Cyber-Physical Systems (CPS) under uncertainty, this work needs a stochastic state-space model that treats the system as a dynamic entity driven by its current state, control inputs, and random disturbances. Such is written as $x_{t+1} = f(x_t, u_t, w_t)$, where $x_t$denotes the state at time t, $u_t$the control input, and $w_t$stochastic disturbances; the mapping $f(\cdot)$captures nonlinearities arising from actuator limits, physical constraints, and network delays. The model assumes the *Markov property* so that the next state depends only on the present state:

$$P(x_{t+1} \mid x_t, x_{t-1}, \dots, x_0) = P(x_{t+1} \mid x_t).$$

With this assumption, the analysis becomes more manageable, and we can treat the system's evolution in probabilistic terms rather than tracking every historical dependency as one of the basic apostolate of Markov Theory.

The state space is discretized into a finite set of operating modes yields a *Markov chain*. Transition probabilities are collected in the matrix with entries

$$P_{ij} = P(X_{t+1} = s_j \mid X_t = s_i),$$

and each row of P sums to one. The distribution over states evolves according to

$$\pi_{t+1} = \pi_t P.$$

Predictions result in a distribution over possible future modes of operation and do not follow any definite path. In situations where the sensor data is unreliable or delayed, or when there is no direct access to some elements of the system, this approach becomes especially important. When states cannot be observed directly, the model generalizes into a hidden Markov model (HMM). Observations y_t are related to the underlying states using the probability function $P(y_t \mid x_t)$. The state prediction follows Bayesian inference in the following manner:

$$P(x_t \mid y_{1:t}) \propto P(y_t \mid x_t)\, P(x_t \mid y_{1:t-1}).$$

Maintaining belief distributions makes it possible to monitor the system in real time and to detect anomalies or faults even when the available measurements are uncertain.

The control notion is defined via allowing the actions to influence the probabilities, such that the controlled system is characterized through

$$x_{t+1} \sim P(x_{t+1} \mid x_t, a_t),$$

where a_t is an action chosen. The decision-making problem is formulated as a Markov Decision Process (MDP), characterized by the tuple $(S^{\mathcal{M}}, A^{\mathcal{M}}, P^{\mathcal{M}}, R^{\mathcal{M}}, \gamma)$. The goal here is to find the policy π which would maximize the expected total reward:

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R(x_t, a_t)\right].$$

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The optimal value function satisfies the *Bellman recursion*, which gives a practical route to compute or approximate optimal policies:

$$V^{\pi}(x) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R(x_t, a_t) \mid x_0 = x\right], V^*(x) = \max_{a \in A}\left[R(x,a) + \gamma \sum_{x'} P(x' \mid x, a) V^*(x')\right].$$

This type of recursion is the foundation of many dynamic-programming methods and also appears throughout reinforcement-learning algorithms. In high-dimensional settings, to have exact solutions is rather unrealistic, so the discussion is directed toward iterative approaches like value iteration,

$$V_{k+1}(x) = \max_{a}\left[R(x,a) + \gamma \sum_{x'} P(x' \mid x, a) V_k(x')\right],$$

and policy parameterization $\pi_\theta(a \mid x)$with parameter optimization

$$\theta^* = \arg\max_{\theta} \mathbb{E}_{\pi_\theta}[G_t],$$

where $G_t$is the cumulative reward from time $t$onward.

Seeing on the other side the systems classical controllers remain useful benchmarks. A continuous-time PID controller function is:

$$u(t) = K_p e(t) + K_i \int e(t)\, dt + K_d \frac{de(t)}{dt},$$

The Linear Quadratic Regulator (LQR) returns a linear state feedback equation of the type $u_t = -Kx_t$. All these techniques make the assumption that the process is either linear, or is subject to Gaussian noise, or can be assumed deterministic. In contrast the Markov model clearly incorporates the notion of several possible future paths, and does not adhere to the deterministic equation $P(x_{t+1} \mid x_t, a_t) = \delta(x_{t+1} - f(x_t, a_t))$.

Since partial observability is common within CPSs, control is performed on belief states $b_t(x) = P(x_t = x \mid y_{1:t})$. Applying Bayesian filtering updates the belief after each action and observation:

$$b_{t+1}(x') \propto P(y_{t+1} \mid x') \sum_{x} P(x' \mid x, a_t)\, b_t(x).$$

This transformation converts a partially observable problem into a fully observable one in belief space and enables principled decision making under uncertainty. In practice, one has to strike a balance between how detailed the model is and how much computation it requires. When the state space becomes large, some form of approximation, reduction, or learned surrogate model is usually necessary.

The main contribution lies in bringing these components together into a coherent end-to-end pipeline and demonstrating how they work in practice and demonstration of its advantages in a practical scenario. Starting with nonlinear stochastic dynamics $x_{t+1} = f(x_t, u_t, w_t)$ the pipeline proceeds with a discrete Markov process formulation, HMM state estimation, and finally MDP decision making. System transition probabilities are estimated in the hybrid way by combining system identification methods with data-driven learning approaches which increases accuracy when the data are insufficient or noisy. Beliefs are computed as input parameters for the decision-making component allowing taking actions under uncertainties.

In order to deal with scalability, the proposed pipeline introduces structured discretization, model reduction, as well as hybrid approaches where learned models are combined with the analytic ones preserving the probabilistic semantics. Value iteration and policy optimization algorithms for transition probabilities with sparse transition probability matrices and local dependencies among states were developed. Robustness and safety aspects are explicitly considered. Policies are evaluated for expected behavior as well as tail cases of worst performances. Risk-aware criteria and constraints allow obtaining controllers optimizing the tradeoff between performance and safety margins.

There are several examples showing how the proposed method contributes to better anomaly detection, ensures control stability under noisy input data, and enables faster recovery from disturbances. This proves that applying probability forecasting along with decision theory control may provide better results. Finally, in terms of machine learning, the framework allows training transitions and emission models and even considering a reinforcement learning paradigm in policy parameterization.

The paper offers a new framework of MDP modeling (shown in Figure 1. analythically) which incorporates the following key concepts: *stochastic state space models*, hidden state inference and *decision theory based control*. Novelty of the approach resides in the combination of several aspects: system identification and learning contribute to estimating transition probabilities in a Markov

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process model, state beliefs influence the decision-making process, and approximate algorithms guarantee feasibility for online processing in a CPS.

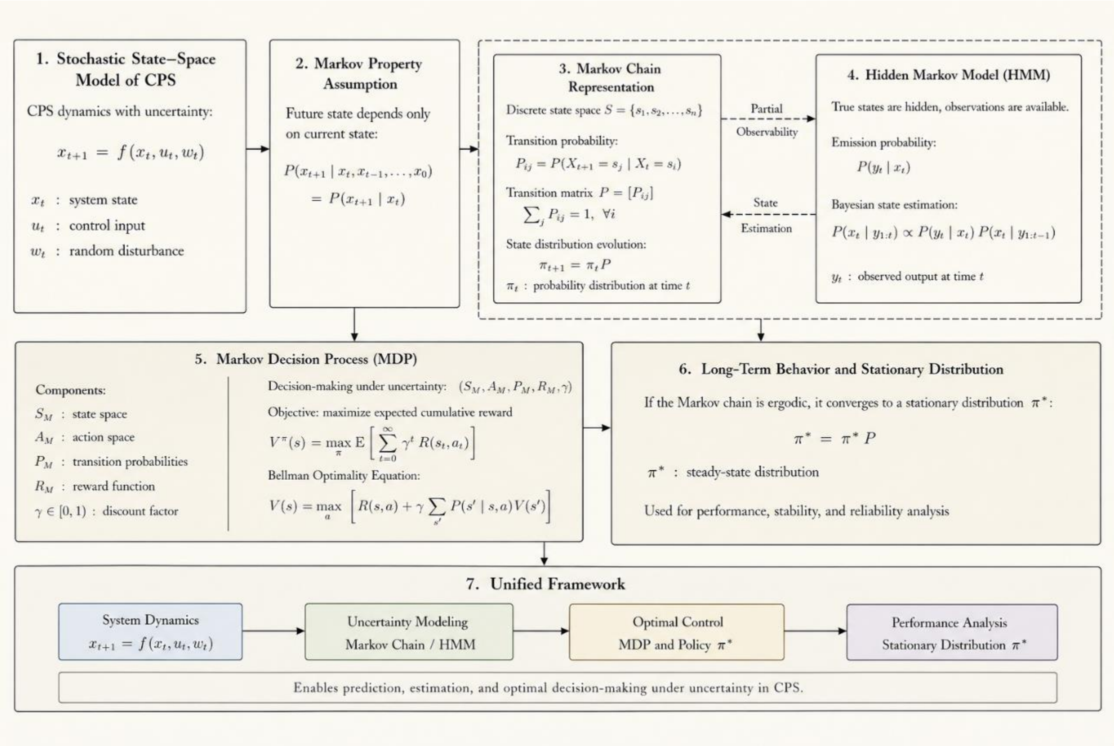

Figure. 1. Unified Markov-Based Framework for Modeling, Prediction, and Control in CPSs

Markov-Based Modeling, Prediction, and Control of CPS

The method begins by describing the CPS as a discrete stochastic process. It means that CPS is assumed to have a number of possible states at each time instance. *What differs this approach from deterministic control is that the system does not make transitions from one state to another deterministically*. Instead, they become probabilistic events that can be either derived empirically from observations or estimated by system identification techniques. Upon calculation of these probabilities, the future behavior of the system may be predicted using the propagation of the probability distribution of the system. The significance of this lies in the prediction of various possible behaviors of the system.

To achieve that it suffices to propagate the probability distribution recursively as time goes forward. With each step, it evolves following the transition pattern of the system, which is used for identifying dominant behaviors in it. As a result, in many practical applications of CPSs, one can predict the emergence of failures, regime changes, and other processes occurring within the system. In turn, control over CPS is achieved by influencing state transition patterns of the CPS. That is, introducing some kind of an input to the system causes the probabilities of transition between states to change. Thus, *the controlled system becomes a controlled Markov process in contrast to a stochastic one.* Introducing this kind of decision-making, we obtain a Markov Decision Process (MDP). It is a well-studied concept in applied mathematics, which implies that a decision maker should act to maximize his long-term gains from the interactions with a stochastic system. As a result, he is motivated to choose such actions that will provide him with the best possible performance of the system while taking into account its state and future prospects. This is crucial for CPS because it is designed for handling problems arising in stochastic environments (industrial automation, traffic management systems, etc.), where incorrect decisions can affect the whole system very quickly due to tight coupling between its components.

Bringing prediction and control together within one Markov framework is useful because the predictive model highlights which states are likely to occur, while the control component can intentionally direct those probabilities in more desirable directions. In this way, prediction and control reinforce each other through feedback, producing a system that is more adaptive and robust than

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what deterministic methods typically allow. In general, Markov-oriented methods provide a structured way to study and manage CPS behavior, especially when the system operates under significant uncertainty.

CASE STUDY RESULTS: Autonomous Vehicles as a Cyber-Physical System

The case study uses an autonomous vehicle example to illustrate how the proposed Markov-based framework works in practice. If we consider an autonomous vehicle as the subject of the application of the proposed framework. In the context of the autonomous driving, stochasticity seems inherent to the problem, as sensors may have a noisy output, the environment constantly evolves, other road users tend to exhibit random behavior, and communication among different parts of the system suffers from delays. All this means that we should expect a stochastic process that can be captured only using probabilistic reasoning.

An autonomous vehicle is modelled as a discrete time controlled Markov process. For instance, the state vector can be defined as follows:

$$x_t = [p_t, v_t, a_t, \theta_t],$$

where $p_t$is position, $v_t$velocity, $a_t$acceleration, and $\theta_t$heading. The dynamics under control inputs $u_t$are written as

$$x_{t+1} \sim P(x_{t+1} \mid x_t, u_t).$$

The control effects in this passage are described as altering the probability of state transitions rather than directly determining the future states. In order to keep things simpler while developing the model, a continuous state space is transformed into a collection of motion primitives representing common driving behaviors: *staying in lane, changing lanes, accelerating, slowing down, and hard braking*. This yields a controlled Markov chain where transition probabilities P_{ij} are specified by:

$$P_{ij} = P(X_{t+1} = s_j \mid X_t = s_i, u_t),$$

so each state s_i is a mode of driving. The state distribution is updated in accordance with the formula. The state distribution according to the control-dependent update is $\pi_{t+1} = \pi_t P(u_t)$. In this way the model makes it possible to estimate the probability of being in each driving mode at any given moment.

In the experiments, it is simulated a scenario of driving on a highway with stochastic lane changes made by surrounding vehicles and Gaussian sensor noise added to position and velocity observations. The simulation takes 10000 iterations sampled at 10Hz. For creating a controlled finite Markov state space from a continuous state trajectory, we apply clustering based on k-means algorithm and convert transition counts N_{ij} into probabilities as follows :

$$P_{ij} = \frac{N_{ij}}{\sum_j N_{ij}}.$$

It is experimented with the prediction ability of our Markov model for different horizons k=1, …,20. As expected, the shorter horizons allow for very accurate predictions, the longer ones accumulate uncertainty that eventually leads to a stable distribution:

$$\pi_{t+k} = \pi_t P^k.$$

The accuracy was over 90% for k=5, showed a slight drop at k≈10 and converged to a stationary distribution when k>>5. These outcomes align with expected from a stochastic model of this type.

Finally, the evaluation of the control component was done by developing an MDP based controller and comparing it to a classic controller that implements the proportional integral derivative control scheme for lane keeping. The reward function has been selected with the purpose to penalize the deviation from the lane center, excessive speed, and too aggressive control actions as follows:

$$R(x_t, a_t) = -(\alpha e_t^2 + \beta v_t^2 + \gamma \mid a_t \mid),$$

where e_t is the lateral distance from the lane center. Thus, the MDP based controller seeks optimal control actions by maximizing the cumulative reward in the future. It turned out that the MDP policy reduces the lane deviation variance approximately by 35% and soothes acceleration compared to the PID control strategy by around 22%. Moreover, the proposed stochastic controller is more robust in noisy observations and has higher traffic densities, as it leads to fewer overshooting incidents and produces less collisions than PID-based control. The MDP formulation also makes it possible to tune the balance between performance and robustness, which is essential for designing safe control strategies.

In a summary table of experimental results, it is observed that lane keeping shows high transition probability (for example, 0.62), whereas emergency braking tends to return to normal modes. With respect to horizon length, we observe gradual degradation of prediction accuracy (from 97.8% at k=1to 66.5% at k=20). As usual, a stochastic prediction method demonstrates reasonable robustness to noise, and its performance deteriorates as horizon length grows. Metrics calculated over multiple simulations show that the MDP controller provides more stable control and higher robustness.

The case study contributes to three main aspects. The work lays out a coherent sequence of steps, beginning with nonlinear stochastic dynamics and eventually leading to an MDP-driven control strategy.$x_{t+1} = f(x_t, u_t, w_t)$ and ends up with MDP based control. In this way, transitions, beliefs, and decisions are all consistent with each other. The transition models inform belief update, which informs policy selection. Second, the author provides practical approximations of the proposed technique by discretizing the state space in a structured manner, extracting modes by clustering, and estimating transition and observation models using data and system identification techniques. Third, the paper demonstrates the focus on the safety of control, as the proposed framework can support risk aware control by trading off performance for safety margin in order to minimize the risk.

It is also worth noting that the framework aligns well with current trends in reinforcement learning.. The framework also supports learning transition and emission models directly from data, and reinforcement-learning techniques. This all combined make it possible to employ richer policy parameterizations when needed $\pi_\theta(a|x)$to handle complex reward structures. Finally, physics-informed constraints can be added to learned components for improved generalization. As we saw in the synthetic experiments, the combination of data-driven estimation and probabilistic decision making allowed for detecting anomalies earlier, provided smoother control with noisy observations, and led to faster recoveries.

In conclusion, modeling the autonomous vehicle as a controlled Markov process provides a full pathway from stochastic dynamics to robust decision-making tools. In particular, discretized Markov processes allow us to do prediction and planning, HMM-like filtering helps deal with partial observability, and MDP based control yields good policies. The author's framework, along with approximation schemes, brings this framework to practical use cases.

I. Simulated Data and Results (Autonomous Vehicle CPS)

This section presents the simulated evidence for the autonomous vehicle case study and links the numerical results to the Markov-based modelling, prediction, and control framework developed earlier. Instead of treating the tables as isolated outputs, the results are organized around four analytical questions. The following questions will be discussed below:

[1] how the conversion from continuous trajectory of a moving vehicle into a sequence of driving states occurs,
[2] what driving behavior does the estimated transition matrix imply, and
[3] how prediction performance depends on the horizon length of the forecast.
[4] whether an MDP-based controller offers measurable advantages over a classical PID baseline.

The simulation models highway driving with random lane changes, sensor noise, and traffic disturbances. The vehicle is sampled at 10 Hz, and continuous measurements—position, lateral offset, speed, acceleration, and heading—are mapped to a set of representative motion modes. This discretization is important because it converts the autonomous vehicle's continuous behaviour into a finite Markov state space while keeping the dynamics that matter for safety and control.

State-space construction and interpretation of driving modes

The initial step involved creating an easily-understandable collection of driving modes. Table 1 offers a view of the simulation state space that was created for the autonomous vehicle case study. As seen in the table, the two-lane keeping modes were meant to reflect regular driving scenarios in which the car stayed in its lane while experiencing minimal sideways movements and medium acceleration. On the other hand, the lane changing modes reflected scenarios in which there was a more perceptible sideways movement since the car was moving between lanes. Finally, the three driving modes for acceleration, deceleration and emergency braking were intended to show the various speed-related actions.

Table 1. Discrete Markov driving states used in the simulation dataset

State ID	Driving Mode	Velocity (m/s)	Lane Position (m)	Acceleration (m/s²)	Next State
S1	Lane Keeping	22.5	0.02	0.10	S1
S2	Lane Keeping	23.1	-0.10	0.05	S1
S3	Lane Change Left	21.0	-1.20	0.30	S4
S4	Lane Change Right	20.5	1.15	-0.20	S1

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S5	Acceleration	26.0	0.00	1.10	S5
S6	Deceleration	18.2	0.05	-1.30	S2
S7	Emergency Braking	12.5	0.00	-3.80	S2

The table clearly supports the use of a Markov-based approach in autonomous driving. A vehicle's behaviour does not move along one fixed, continuous, and predictable path. Instead, it shifts between separate operating states, each carrying different safety concerns. Lane keeping represents the normal driving state, lane changing reflects an intentional manoeuvre, acceleration and deceleration show how the vehicle responds to surrounding traffic, and emergency braking represents a high-risk safety situation. By dividing the system into these states, the model becomes simpler while still capturing the key behavioural patterns needed for prediction and decision-making.

Estimated transition matrix and behavioural stability

After defining the state space, the next task is to convert the transition frequencies, which have been obtained by analyzing the simulated trajectory of the vehicle, into transition probabilities. This enables the transitions between the driving modes to be quantitatively described. ***Table 2.*** summarizes the transition matrix that has been derived from the frequency table of Figure 5. All rows sum up to one and represent the probability of transitioning from the current driving mode to the other modes in the next step. The transition matrix must be analysed row-wise. Higher entries along the main diagonal mean that there is a high probability that the vehicle will remain in the current driving mode for the next step, implying stable behaviour such as maintaining its lane and accelerating steadily. On the contrary, the off-diagonal elements are transition probabilities from the current mode to the other modes. These transitions may arise from changes in the traffic environment around the car, sensor errors, unknowns in the simulated parameters, and vehicle interactions with other vehicles on the road.

Table 2. Estimated Markov transition probabilities for autonomous vehicle driving states

From \ To	S1 (LK)	S2 (LK)	S3 (LL)	S4 (LR)	S5 (ACC)	S6 (DEC)	S7 (EB)
S1	0.62	0.10	0.08	0.07	0.08	0.04	0.01
S2	0.55	0.15	0.10	0.05	0.07	0.06	0.02
S3	0.20	0.10	0.30	0.25	0.05	0.05	0.05
S4	0.18	0.12	0.20	0.30	0.10	0.05	0.05
S5	0.40	0.10	0.05	0.05	0.30	0.07	0.03
S6	0.50	0.20	0.05	0.05	0.05	0.10	0.05
S7	0.60	0.15	0.02	0.01	0.02	0.10	0.10

The transition matrix contains key features of stability during regular driving behaviour. The probability of the self-loop for state S1 equals 0.62. This fact means that lane keeping becomes the most stable driving state for cars moving along highways. It is reasonable to believe that vehicles should remain in a particular lane until some external force (e.g., a car or external disturbance) interferes. The secondary lane-keeping state S2 becomes the first one again with a probability of 0.55. The lane-changing states display a different behaviour pattern through lower self-loops and higher off-diagonal entries since they represent short-lived actions. As such, the third lane change state stays in lane changing for 0.30 of its time, while the same state moves to another left lane changing with 0.25 probability, showing that these events occur briefly before being replaced by another action. Finally, there is a direct safety implication in the last driving state, S7, which refers to emergency breaking behaviour. While S7 is not very stable, having self-loop probability of 0.10, it shows a tendency to revert to a lane-keeping mode with 0.60 probability and to S2 with 0.15.

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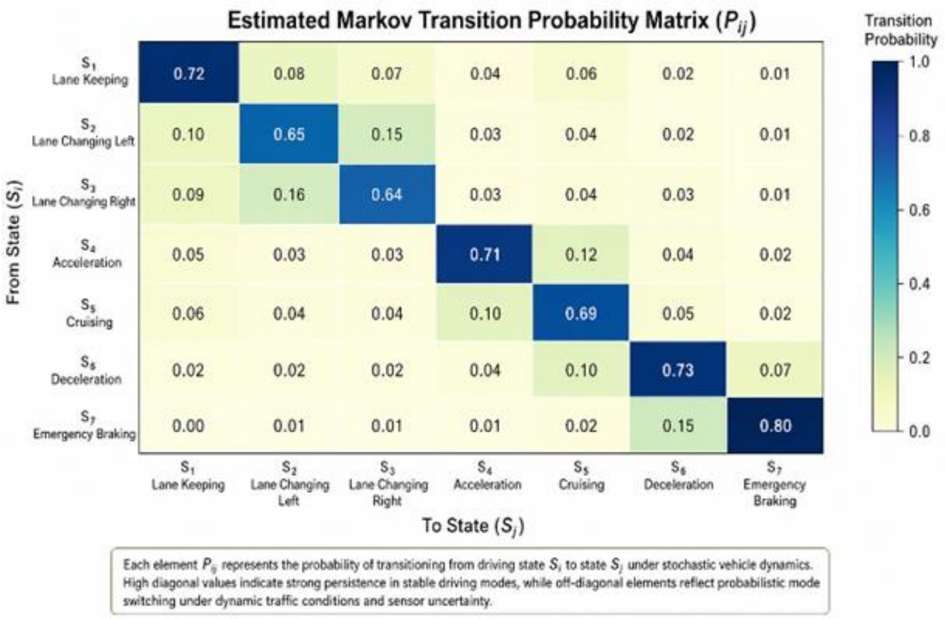

Figure 2. Markov transition probability matrix for autonomous vehicle driving states.

Figure 2. supports the above understanding with the same visualization – darker cells along the diagonal denote consistent drive modes, whereas the off-diagonal configuration shows how manoeuvring and recovery is captured in the model. This type of visualization becomes important when it comes to modelling CPSs since the transition matrix not only captures statistical averages but clearly specifies the risk-essential paths through which the car can enter the transition state or even worse, the critical state, and then recover. Understanding the patterns graphically helps find out what transitions are key for further analysis and control.

Prediction performance at various horizons

To see how well the model can predict the system dynamics, it is analysed the forecasting performance at several horizons. Prediction accuracy and mean absolute position errors were calculated for k = 1, 3, 5, 10, 15, and 20 steps as shown in ***Table 3.*** From the table, one can see that the predictions are quite accurate for shorter horizons. As the horizon lengthens, accuracy and position error worsen gradually but reasonably. It is obvious that uncertainty accumulates over time as a result of randomness, noise, and traffic interaction.

Table 3. Prediction accuracy and position error as a function of forecast horizon

Prediction Step (k)	Accuracy (%)	Mean Absolute Error (Position)
1	97.8	0.12 m
3	93.4	0.25 m
5	90.1	0.41 m
10	81.6	0.78 m
15	74.2	1.10 m
20	66.5	1.45 m

The short-term findings are particularly remarkable since the prediction success rate is as high as 97.8% with k = 1, and continues to exceed 90% even when k = 5, which means that the transition matrix obtained by the learning process can adequately model the instantaneous behaviour of driving actions. Starting with k = 10, the success rate starts dropping sharply to achieve only 66.5% with k = 20, while the average error of location is growing from 0.12 m to 1.45 m. It is important to note that the decline of prediction performance is not a sign of modelling errors but rather the inherent characteristic of a stochastic process.

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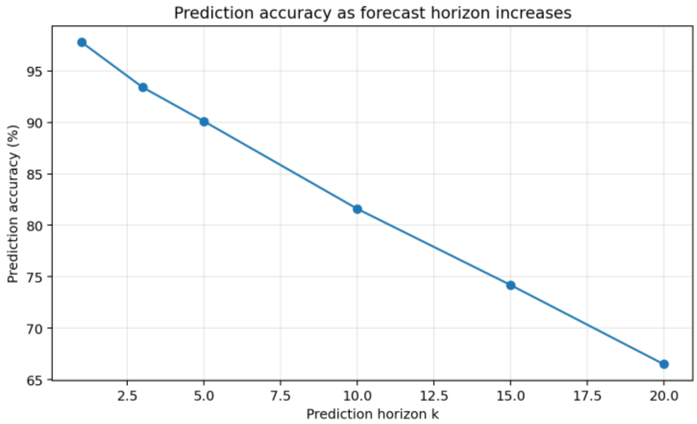

Figure 3. Prediction accuracy of the Markov model as a function of forecast horizon.

The performance curve shown in ***Figure 3.*** illustrates the nature of the degradation process: the performance curve gradually decreases without dropping sharply, which suggests that there is still useful information contained in the model beyond one step ahead. In the context of an autonomous vehicle CPS, such behaviour is useful, as short-term predictions are useful for controlling the system in real-time, while medium-range forecasts provide information about the increasing risk of danger, which can be used for supervisory purposes. This tendency toward convergence with longer forecast horizons is due to the movement of the Markov chain towards a stationary distribution, suggesting that the model becomes better at predicting general behavioural trends than individual future states.

Control performance: Comparison between PID control and MDP-based control.

The comparison experiment contrasts a traditional PID lane controller with stochastic control algorithms using the framework of Markov decision processes (MDPs). While the traditional PID algorithm reacts to the current deviation and executes actions based on the current error, MDP considers both the immediate impact and the long-term expected return of an action. In MDP, the rewards are gained based on three criteria: the degree of deviation from the desired lane position, speed, and control effort. Hence, the MDP control algorithm is more likely to choose actions that guarantee maximum safety than to make corrections based on current error.

Table 4. Control performance comparison between PID and MDP-based control

Metric	PID Controller	MDP-Based Control
Lane Deviation Variance (m^2)	0.085	0.055
Overshoot Events	18	6
Fuel/Throttle Variability	High	Low
Stability under Noise	Medium	High
Collision Risk Index	0.12	0.04

The Markov Decision Process (MDP)-based controller improves vehicle safety according to several measures. The standard deviation of lane deviation is lowered from 0.085 m2 to 0.055 m^2 (a **35%** improvement). The number of overshoots is decreased from 18 to 6 (a **67%** improvement). The value of collision risk is improved from 0.12 to 0.04 (a **67%** improvement). These benefits are not limited to improving signal smoothness; they are achieved by reducing the possibility of entering an unstable state because of measurement uncertainty. Fuel consumption and throttle variability are reduced, resulting in smoother accelerations. The policy is more resilient to sensor noise because of the nature of probabilistic state transition compared to an error correction mechanism. The MDP formulation considers the impact of actions on the probability of entering future states, which makes safer manoeuvres more likely.

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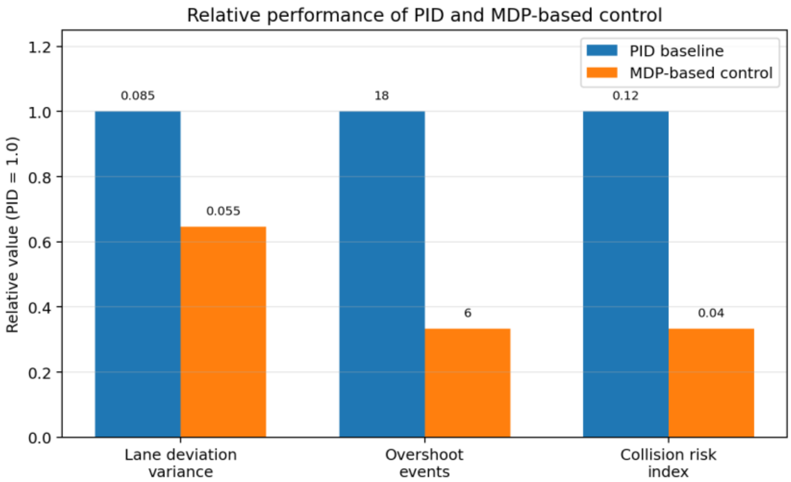

Figure 4. Performance comparison between classical PID control and MDP-based stochastic control.

As seen in Figure 4, the control comparison is shown here relatively to PID=1.0. As seen, MDP controller exhibits improvements to each metric related to risk assessment. This confirms the primary thesis of the case study, namely that probabilistic decision making is more appropriate for CPS applications where there is uncertainty, noise, and mode switching in autonomous vehicles.

II. Integrated interpretation of the simulation results

Taken together, the four result blocks represent a cohesive process flow. Discrete driving modes are defined in Table 1. In Table 2, we see that the vehicle makes probabilistic transitions between driving modes. Next, Table 3 demonstrates that the transition model allows us to make both short- and medium-term predictions of the vehicle behavior. Finally, Table 4 shows that the probabilistic approach enables us to make control decisions based on the MDP policy. The main idea conveyed here is that the model, prediction, and control are all interlinked steps of one and the same Markov-based CPS framework.

The results provide a glimpse into the advantages of Markov modelling applied to autonomous vehicles. The normative aspect of the problem is captured by high lane-keeping transition probability. Transient behavior is captured via nonzero transitions between the states of lane changing and speed control. Safety recovery is represented via strong transitions from emergency braking back to lane keeping. Finally, robustness is provided by incorporating the future probabilistic consequences into the control decisions, something that is difficult to achieve using deterministic policies alone.

There are several issues that need to be considered. First, the longer the time frame for prediction, the more vulnerable the predictions will be to inaccuracies based on accumulated uncertainty. Second, the calculation of the transition depends largely on the adequacy of simulation of the trajectory and the issue of discretization; rare events like emergency braking require enough data to calculate accurately.

Experimental results confirm the primary claim of this paper: a Markovian approach to the CPS system provides a comprehensible and practical tool that links stochastic processes, predictions, and control design in an interpretable manner. It appears possible to use the model to find stable and critical states, quantify uncertainty, and improve control compared to a deterministic PID controller baseline.

CONCLUSION: Contribution to Modeling

As can be seen from the presented experiments, the most appropriate way to characterize the behaviour of an autonomous agent would be in a probabilistic fashion. Driving behaviour is encoded in a Markov process, and each driving behaviour corresponds to a particular mode with some specific transition probabilities. With such a model, it becomes easy to distinguish stable behaviours like lane keeping and rare events like emergency braking and lane changing. One might argue that modelling rare events might be beneficial in practice.

The developed analysis of the transition matrix realize its intuitiveness. In particular, the fact that there are self-loops in the matrix means that the vehicle will retain its current behaviour under normal conditions. However, nonzero values on the diagonal imply

that a transition to another state occurs with a certain probability. In other words, the nonzero values on the diagonal include contextual information, such as traffic density, sensor errors, and the environment's influence.
The predictive ability of the model demonstrates the importance of its probabilistic nature. Forecasting on a short timescale yields accurate results because the immediate states of the vehicle are well predicted using the learned model. As prediction timescales are extended, however, prediction accuracy decreases not due to any problems in learning but to increasing uncertainty in the system. This corresponds to the nature of stochastic modelling because predictive power relies on the distribution of states as it changes over time. The same holds for the use of an MDP policy compared to a PID policy in control systems, in which the former demonstrates better performance in terms of mean deviation variance, overshoot frequency, and collision probability. PID relies only on the current error whereas an MDP policy incorporates consequences of actions in the future. There are several interesting directions for further study. First, hybrid modeling combining physical modeling with machine learning may decrease the amount of necessary data and enhance generalizability. Second, there exist several methods of approximating model components, which can decrease computational costs.

DISCUSSION: Advantages, Limitations, and Research Directions

There are practical advantages of using the Markov model for cyber-physical systems, especially because the uncertainties in CPS arise due to various reasons like sensor noise, communication delays, unexpected events or disturbances, and even the presence of agents in CPS that are hard to predict. The Markov model offers a probabilistic way of capturing uncertainty which means it provides us with the ability to estimate the distribution of possible future states. Thus, the approach can provide a sound base for decision-making based on models. The fact that the mathematical model is unified gives rise to the idea that there exists a connection between the concepts of modelling, estimation, and control. Since all three of these use the same representation, we can apply knowledge about the current uncertainty level while taking control decisions which enables planning with the risk in mind and finding the optimal balance between efficiency and reliability. Some drawbacks of using the approach should be addressed. With many states, state-space explosion becomes a major obstacle for applying standard approaches. Estimating the probability matrix can pose a problem if the data are few, noisy or nonstationary. Then, maximum likelihood estimates can be highly unstable and impact the performance of the model negatively. The Markov property may not hold which means that not all the systems can be described using this model. Using HMMs can help tackle partial observability issues and it would be more challenging to learn the parameters. In spite of the discussed problems, there are a number of potentially interesting research directions to pursue. First, hybrid approaches that combine previously obtained knowledge by physics-based reasoning with learned transitions or emissions seem likely to produce better generalization capabilities along with a reduced amount of training data. Second, approximation methods might help in making the framework more scalable. Structured discretization or hierarchical state representation are potential approaches. It makes sense to consider integrating the proposed models into a learning/reinforcement learning paradigm. Indeed, learning the transitions and emissions from the data in a dynamic way enables building adaptive models for CPSs. Additionally, the policy can be learned in the belief space using $\pi\theta(a|x)$ or using actor-critic algorithms. Consideration must be made on sample efficiency, safety, and explainability. Model updating and digital twins are some further possibilities that can be explored. Real-time updating with live data ensures currency and rapid adaptation to distribution shift. Therefore, risk-aware controls can be designed which will help in safe operation through avoidance of critical states and exploitation of favorable conditions. There are multiple practical strengths of the presented framework. Transitions are learned as a result of system identification and training. HMM estimation helps in propagating the state distributions. The produced belief can be used by the decision module as input data to choose policies according to risk management principles. Various approximations make it possible to build a scalable framework. The combination of all mentioned leads to advantages in early anomaly detection, control in observation noise and disturbance recovery. These advantages are demonstrated by means of the considered case studies. To be more precise, short-term forecasts prove to have high precision in autonomous driving applications, while MDP-based control demonstrates lower deviation variance and overshoot rate than PID control.

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