General dynamic neural networks for explainable PID parameter tuning in control engineering: an extensive comparison

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Abstract

Automation, the ability to run processes without human supervision, is one of the most important drivers of increased scalability and productivity in technology. Modern automation largely relies on forms of closed loop control, wherein a controller interacts with a controlled process via actions, based on observations. Despite an increase in the use of machine learning for process control, most deployed controllers still are linear Proportional-Integral-Derivative (PID) controllers. PID controllers perform well on linear and near-linear systems but are not robust enough to be appropriate for more complex controlled processes. As a main contribution of the present paper, we examine the utility of extending standard PID controllers with recurrent neural networks—namely, General Dynamic Neural Networks (GDNN); we show that GDNN (neural) PID controllers perform well on a range of complex control systems and highlight what is needed to make them a stable, scalable, and interpretable option for modern control systems. To do so, we provide a comprehensive study using four different benchmark processes. All four control environments are evaluated with and without noise as well as with and without disturbances. The neural PID controller performs better than standard PID control in 15 of 16 tasks and better than model-based control in 13 of 16 tasks.

As a second main contribution of this work, we address the Achilles heel that prevents neural networks from being used in real-world control processes so far: lack of interpretability. We use bounded-input bounded-output stability analysis to evaluate the parameters suggested by the neural network, thus making them understandable for human engineers. This combination of rigorous evaluation paired with better explainability is an important step towards the acceptance of neural-network-based control approaches for real-world systems. It is furthermore an important step towards explainable and safe applied artificial intelligence.

1 Introduction

Modern production engineering is becoming increasingly complex [1]. The physical processes underlying cutting-edge production engineering cannot be appropriately expressed with simple models [2]. In response, new control methods have been introduced. Unfortunately, these new, more complex control methods are more challenging to design and apply, and require control engineers [3]. Limited by the number of control engineers and their cost, industry has widely chosen to instead retain simple, understandable linear controllers, despite their inability to appropriately model the involved processes. This choice comes at the cost of the controlled processes needing close monitoring and human assistance whenever the system changes in an unforeseen way. Both expert-designed control methods and closely-monitored simple controllers fail to scale.

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One way to bridge this gap is the application of modern machine learning techniques [4]. Extending the capabilities of well-accepted and used controllers with machine learning yields high potential in manufacturing. In this paper, we will further investigate such an extension: the use of neural networks to adapt the parameters of a Proportional-Integral-Differential (PID) controller not only before deployment but online during the ongoing control.

The PID controller is one of the most widely used controllers [5]. A PID controller calculates its control output \( u \) based on the current error \( e \), the error derivative and the error, integrated over time. Each measure is multiplied with a constant \( (K_P, K_D, \text{and} K_I) \) and then summed up. While this controller is simple and well understood, its advantages come at the price of limited capabilities. PID controllers perform well only on linear systems or systems that are linearized. As they are usually adjusted before deployment, they handle neither disturbances nor varying system dynamics well.

Several prior studies have shown that neural networks can improve performance when used to tune the parameters of traditional PID controllers online. Simple feed-forward networks can adjust the PID parameters in multiple settings [6, 7]. More sophisticated neural networks like strictly recurrent, diagonal [8] and quasi-diagonal [9] recurrent networks have also been investigated. However, all these specific design choices result in very specific behaviour and learning [10] and are not expected to generalize well over different control environments. To evaluate whether the use of neural networks with all possible connections is applicable to control engineering tasks in general, a broad range of different challenges is required. Previous work demonstrated the applicability of neural-network—based parameter tuning for one well-defined control task at a time, e.g. pendulums [7], two-tank systems [11] or magnetic systems [6]. However, no single approach has been applied successfully to multiple representative control engineering problems in the literature.

Despite the potential benefits, neural networks are not used regularly for parameter tuning in real-world control systems; one reason for this lack of uptake is the challenge of explaining the control decisions or stability implications of previously demonstrated neural models. The domain of control engineering demands explainability to ensure system safety [12]. As neural networks introduce a black box to the system [13], their use for PID parameter tuning is not yet widely accepted. It is thus paramount to be able to check and explain the parameter choices a neural network outputs when granted access to a PID controllers parameters. Perhaps surprisingly, we suggest that the use of networks that allow all possible connections between internal units will in fact enable designers to achieve a better performance without significantly increasing the design complexity or design interpretability when deploying a controller.

In this paper, we advance the above point by investigating the use of General Dynamic Neural Networks (GDNNs) for online parameter tuning in PID controllers. These neural PID controllers are evaluated on four different closed loop control engineering tasks. Each task represents a different, common challenge in control engineering, namely non-linear behaviour, unstable equilibrium, dead time, and chaotic behaviour. We compare the performance of our neural approach with a standard PID controller, which acts as a baseline, and with a system-appropriate model-based controller, which should provide the best possible performance. To evaluate robustness, each comparison is performed with and without significant sensor noise and with and without disturbance. All controllers are evaluated quantitatively for all scenarios, making this study unique in its comprehensiveness. We furthermore investigate the stability of the neural PID controller as it tunes the parameters on one representative scenario. This assessment provides an explanation of when the system is stable with respect to the PID parameters, making the neural network outputs understandable to control engineers. The present paper therefore addresses key attributes of safe and explainable artificial intelligence.

### 2 General Dynamic Neural Network for PID parameter tuning

To extend the standard PID controller without adding complexity, the neural networks inputs are restricted to signals which are already available in the closed loop. This setup defines the size of the input- and output layers. As seen in Figure 1(a), the neural network inputs are the system output \( v \) and the error \( e \). The neural network outputs are the three PID parameters \( K_P, K_I, \text{and} K_D \). For the purpose of this study, all tested neural networks had one hidden layer with 4 neurons, as this size is sufficient for the network to be a universal approximator [14]. A neural network of this size is also cheap and fast to compute. The network architectures differed only in additional recurrent or feedback connections. An example can be seen in Figure 1(b). In this case, the simple feed-forward
Figure 1: A neural network is integrated into standard closed loop control (a). The neural network receives the system output and the error as input and outputs the three PID parameters $K_P$, $K_I$, and $K_D$. The double-lined arrows indicate that the associated variable could be a vector, while the single-lined arrows indicate scalar variables. An example neural network (b) shows one possible set of connections. All networks have 9 neurons in three layers. All hidden neurons have delayed feedback connections, denoted $g^{-1}$, to the input layer to capture temporal information.

The network was extended by feedback connections from each neuron in the hidden layers to the inputs with a time delay of $g = 1$. This delay proved to be sufficient for the control task. For all neurons, the activation function tanh was chosen, following the rationale of [15]. Weights are initialized randomly with a mean of zero and a standard deviation of one.

A standard approach to train neural networks is backpropagation [16]. However, in the present setting, backpropagation cannot be applied naively. The neural network outputs are the PID parameters $K_P$, $K_I$, and $K_D$ while the error to be minimized is the difference between the setpoint and the system output. Therefore, a loss function with respect to the neural network output cannot be formulated directly, as the ideal solution, i.e. the ideal PID parameters, is not available. For this reason, the neural network is trained using a numerical Levenberg-Marquard algorithm [17]. At each time step, the Jacobian matrix is computed and the control error $e$ with respect to each weight is evaluated. Each weight is then adapted to decrease the control error. To train the neural network, data is collected using the differential equations and an excitation signal as described in [18]. The system is excited with controller inputs $u$ of various lengths and amplitudes to provide sample system outputs. This follows the idea of system identification using a Dirac impulse [19]. We collect 35,000 data samples that are split into training, validation, and test sets with a ratio of 15%, 30%, and 55%, respectively.

### 3 Experiments

To evaluate the performance of the neural PID controller, we use four typical control problems. Each system offers a different control challenge. Each individual system is controlled with and without noise. The noise is Gaussian white noise with a signal to noise ratio (SNR) of 20dB and corresponds to noisy measurements from the sensors. The noise is added to the system output.

To further evaluate the robustness of the controller, we inflict upon each system a suitable disturbance. For each system, the disturbance is increased in size from zero until only one control approach is still able to stabilize the system. Disturbances of this magnitude are then used in the experiments. These disturbances are not included in the training data for the neural PID controller. All experiments are run over 50 independent runs to ensure statistical relevance. The system differential equations are solved using the Dormand-Prince solver. To simulate real-world conditions of a discrete sample time, the controller output can be adapted every 0.01s. This intervention time is chosen to represent the limitations of real-world actuators, which cannot adjust their values on an arbitrarily small timescale. The solver is run iteratively for 0.01s, using the result of the former step as starting conditions. During each 0.01s intervention time window, the controller output $u$ is kept constant.
Figure 2: Experimental systems to evaluate the control approaches. Each of the four system represents a specific control challenge. The Two-Tank System (a) is a nonlinear system. The inverted pendulum on a cart (b), has an unstable equilibrium. To evaluate the compensation of time delay, a first order LTI system with non-negligible time delay (c) was chosen. The chaotic thermal convection loop (d) represents a system with chaotic behaviour.

The training is done on an Intel Core i5-4570 with a 3.2 GHz clock rate, 6 MB of shared L3 cache, 32 GB DDR3 RAM. Once learned, the neural networks run on a Raspberry Pi 3 Model A+.

**Two-Tank System:** The first system is a nonlinear two-tank system, as seen in Figure 2(a). The controller has access to a pump, regulating the input, while the measured output is the water level in the second tank. This system is a standard benchmark system in control theory. It corresponds to various industrial processes, e.g. bio-reactors, filtration, and nuclear power plants. There exist a number of control approaches for this system, including direct control via neural networks [20], adaptive output feedback [21], and backstepping [22], which will be used as comparison.

To evaluate the robustness of the compared control approaches, the two-tank system is disturbed continuously between \( t = 20 \) s and \( t = 40 \) s. As a disturbance, the controller output is set to zero, which would correspond to a drain of the water supply. The water levels in the tank are therefore independent from the control inputs for 20s. The voltage for the pump, \( u \), was limited to the range \([-500V, 500V]\) to simulate a pump appropriate to the tank dimensions.

**Inverted Pendulum on a Cart:** The second system is a nonlinear inverted pendulum on a cart. The control task is to stabilize the inverted pendulum at its unstable equilibrium by applying a force on the cart. The cart’s movement is restricted to 0.5m in either direction. This system is a widespread benchmark system in control theory due to its nonlinearity and unstable equilibrium [23][24]. Practical applications for inverted pendulums include, rocket control during initial stages of flight or keeping a walking robot in an upright position. For comparison, a linear–quadratic regulator (LQR) [25][26] and a double PID controller [26] are used.
The system is disturbed by a force of 8.5N to the pendulum at time $t = 10$s. This disturbance can be interpreted as a strong and unexpected wind condition during the launch of a rocket. The controller output $u$ was bounded within $[-50N, 50N]$, which corresponds to a typical actuator of that size.

**System with Non-negligible Time Delay:** The third system is a first order linear time invariant (LTI) system with a non-negligible time delay. Time delay is a problem in control theory that is not always considered, while designing controllers [27]. Time delays can result in decreased performance and system instability if the controller is not able to cope with it. The benchmarks for this system are a PID controller [28] and a smith-predictor [29]. This system is disturbed by a (dimensionless) disturbance of $-5$ between $t = 50$s and $t = 75$s continuously. Such a disturbance can be thought of as a temporary blockage in a fluid transport system. The exact system specifications can be found in [28]. The controller output $u$ was bounded between the range of $[-10, 10]$.

**Chaotic Thermal Convection Loop:** The fourth system is a chaotic thermal convection loop, as shown in [2](d). Its dynamics are described by the equations

$$
\begin{align*}
    x_1(t) &= p(x_2 - x_1), \\
    x_2(t) &= x_1 - x_2 - x_3(x_1 + \beta), \\
    x_3(t) &= x_1 x_2 + \beta(x_1 + x_2) - x_3 - u,
\end{align*}
$$

with the $p = 10$ and $\beta = 6$ as appropriate constants [30]. Chaotic behavior may lead to vibrations, oscillations and failure in systems and is therefore an important aspect of control theory. As chaotic behavior is unpredictable, mathematical models are only sufficient to a certain point, hence closed loop control is a desirable approach [31]. Usual control approaches for the chaotic thermal convection loop are nonlinear feedback controllers [32] and backstepping [33][34].

To evaluate the robustness of the applied control approaches, the system is disturbed with a force of 100W continuously between $t = 5$s and $t = 5.5$s. This perturbation can be interpreted as a temporary change in the cooling water temperature. To simulate real actuators with a limited capacity, the controller output $u$ is limited between $[-100W, 100W]$ to simulate an appropriate heating element.

### 4 Results and Discussion

The results for all experiments can be found in Table [1]. For each system the mean and variance are shown for all controllers in all tested scenarios. The best control approach is highlighted in bold. For all values, a two-sample t-test was performed and a control approach is only considered to be superior for $p < 0.05$. From Table [1] it can be seen that the neural PID controller performs best in 12 scenarios, pairs with the standard PID controller in one and performs second best in two scenarios. To compare control approaches, there are common measurements that are used in control engineering, e.g. rise time, overshoot, settling time [5]. However, these measurements all address the error between the setpoint and the actual systems output with different emphases. We therefore used the root-mean-squared-error (RMSE) between the setpoint and the system output to summarize these error measures in a single number without losing information.

**Two-Tank System:** For the two-tank system, a backstepping controller is chosen for a comparison, as this approach takes the nonlinear behavior of the system into account and has demonstrated to be well suited for this system [22]. The PID controller is parameterized with the constants $K_P = 3.65, K_D = -2$ and $K_I = 0.4$, found by the MATLAB control system toolbox. All controllers are able to control the system, while the neural PID controller exhibited the smallest error for all scenarios. However, the advantage the neural PID controller yields is relatively small, as can be seen in Table [1]. As this system is the easiest to control, it can be expected that the standard PID controller and backstepping perform on a similar scale.

**Inverted Pendulum:** The inverted pendulum on a cart is controlled by a standard PID controller stack [23], and a LQR [26] for benchmarking. The PID controller, responsible for the position, has the values are $K_P = -2.4, K_D = -0.75$ and $K_I = -1$ and the controller for the angle is set to $K_P = 25, K_D = 3$ and $K_I = 15$ [23]. All three approaches are able to initially stabilize the system. For the scenario without disturbance, the neural PID controller performs equally to the standard PID controller when there is no noise present. For the scenario with only noise, the neural PID controller
All controllers are capable of stabilizing the system, as can be seen in Figure 3(a). The backstepping in the scenario with noise but without disturbance performs slightly better (out of four scenarios, the neural PID controller demonstrates superior control performance. Only controller performs best as it finds a good balance between settling time and overshoot. The neural PID approach has the least overshoot but takes a long time to reach the steady state. The standard PID controller is more aggressive, resulting in a higher overshoot but still a smaller error. The neural PID controller is superior in all scenarios, when compared to the standard PID controller. When compared to the Smith predictor [35], the neural PID controller performs better only for the scenarios without noise. However, as the Smith predictor has knowledge about the exact time delay, it has a significant advantage over the neural PID controller.

### Chaotic Thermal Convection Loop

The PID parameters yielding the lowest error for the chaotic thermal convection loop are $K_P = 25.3$, $K_D = 8.9$ and $K_I = 0.7$—the controller is therefore a PD controller. The system is initialized outside of its inherently stable region (region of attraction) with the initial conditions $x_1 = x_2 = x_3 = 5$. Without control, the system will therefore not converge to the desired steady state $x_1 = x_2 = x_3 = 0$.

All controllers are capable of stabilizing the system, as can be seen in Figure 3(a). The backstepping approach has the least overshoot but takes a long time to reach the steady state. The standard PID controller is more aggressive, resulting in a higher overshoot but still a smaller error. The neural PID controller performs best as it finds a good balance between settling time and overshoot.

Out of four scenarios, the neural PID controller demonstrates superior control performance. Only in the scenario with noise but without disturbance does backstepping perform slightly better (0.89

### Table 1: Control results for the four benchmark systems over 50 independent runs

| Control Benchmark | RMSE on test data over 50 independent runs |
|-------------------|---------------------------------------------|
| **Disturbance**   | - | - | ✓ | ✓ |
| **SNR**           | - | 20 dB | - | 20 dB |
| **Two-tank system** | | | | |
| Mean              | Neural PID | 0.74 | 0.86 | 0.84 | 1.00 |
|                   | Standard PID | 0.95 | 0.99 | 1.00 | 1.10 |
|                   | Backstepping  | 1.10 | 1.10 | 1.20 | 1.10 |
| Variance          | Neural PID | 0.0036 | 0.0040 | 0.0056 | 0.0460 |
|                   | Standard PID | 0.0025 | 0.0023 | 0.0052 | 0.0063 |
|                   | Backstepping  | 0.0016 | 0.0018 | 0.0036 | 0.0024 |
| **Inverted pendulum** | | | | |
| Mean              | Neural PID | 0.03 | 0.02 | 0.09 | 0.27 |
|                   | Standard PID | 0.04 | 0.04 | 140 | 140 |
|                   | LQ regulator  | 0.05 | 0.05 | 140 | 140 |
| Variance          | Neural PID | 0.0004 | 0.0003 | 0.0490 | 0.0007 |
|                   | Standard PID | 0 | 1.1 · 10^{-7} | 0 | 0.0023 |
|                   | LQ regulator  | 0 | 3.3 · 10^{-9} | 0 | 0.0022 |
| **LTI system with input delay** | | | | |
| Mean              | Neural PID | 0.13 | 0.15 | 0.26 | 0.28 |
|                   | Standard PID | 0.22 | 0.23 | 0.36 | 0.38 |
|                   | Smith predictor | 0.18 | 0.19 | 0.19 | 0.20 |
| Variance          | Neural PID | 0.0006 | 0.0005 | 0.0007 | 0.0003 |
|                   | Standard PID | 0.0007 | 0.0006 | 0.0004 | 0.0003 |
|                   | Smith predictor | 0.0006 | 0.0005 | 0.0005 | 0.0003 |
| **Chaotic thermal convection loop** | | | | |
| Mean              | Neural PID | 0.23 | 0.90 | 1.90 | 1.70 |
|                   | Standard PD | 0.24 | 1.60 | 13.00 | 4.20 |
|                   | Backstepping  | 0.26 | **0.89** | 9.80 | 9.80 |
| Variance          | Neural PID | 1.2 · 10^{-5} | 0.0003 | 0.16 | 0.22 |
|                   | Standard PD | 0 | 2.00 | 0 | 1.40 |
|                   | Backstepping  | 0 | 0.0001 | 0 | 1.4 · 10^{-5} |
Figure 3: Control performance for the disturbed chaotic thermal convection loop. Subfigure (a) shows the setpoint and the system output for all controllers. Subfigure (b) shows the controller outputs for all three controllers. In subfigure (c), the PID parameters, applied by the neural network are shown.

Between the time $t = 5\, \text{s}$ and $t = 5.5\, \text{s}$, the control output is set to $u = -100\, \text{W}$ to simulate the disturbance described earlier. The standard PD controller becomes meta stable and its controller output iterates between the maximum value of $100\, \text{W}$ and the minimum value of $-100\, \text{W}$. Although backstepping is proven to be globally, asymptotically stable in the Lyapunov sense [36], it also becomes meta stable. This can be explained by the real world conditions. As the controller can change its control output only every $0.01\, \text{s}$ the backstepping approach fails, resulting in switching inputs between the maximum value and the minimum value, as seen in Figure 3(b). Both controllers (PID and backstepping) use excessive amounts of energy without being able to stabilize the system.

The neural PID controller is able to stabilize the system after the disturbance. Figure 3(c) shows how the neural network changes the PID parameters in response to the system output. When $x_1$ is far from the setpoint, the $K_P$ parameter has a high absolute value to force the system towards its steady state. To further increase the controller output at $t = 7.9\, \text{s}$, where the system reaches its furthest distance from the set point $K_I$ is increased. After the system reaches its steady state again, all PID parameters are adjusted back to their stationary value to ensure asymptotic performance. The neural PID controller furthermore uses significantly less energy to control the system.

Despite the experimental evidence that suggests the enormous benefit of using neural networks to adapt PID parameters online, this approach is not yet used on real-world systems. This is due to the black box character of neural networks and the stringent safety requirements for control processes. One of the most important safety requirements of a closed loop control approach is input-output stability. It describes whether the system output is bounded for all bounded inputs. A system can be evaluated for stability by analysing the closed loop transfer function, i.e. the relation between the system output to its input. For the chaotic thermal convection loop, this closed loop transfer function is dependent on the system’s transfer function, linearized around a steady state $x_1 = x_2 = x_3 = 0$ and the controller transfer function, characterized by the PID parameters. As the PID parameters are changed by the neural network, stability has to be evaluated for every set of parameters. The change in PID parameters furthermore renders a Lyapunov stability analysis impractical, as a well-behaved controller is not guaranteed for changing parameters.

As an important contribution, we therefore perform an analysis of the input-output stability for the controller. This analysis can be seen in Figure 4. The Figure shows the systems output and the stability, with respect to its linearized steady state over the experiment. The closed loop transfer function is not stable in the beginning, during settling and after the disturbance. This can be expected,
Figure 4: Stability analysis for the chaotic thermal convection loop with disturbance. The dashed line shows the system's output, when controlled by the neural PID controller. The closed loop transfer function is not guaranteed to be stable within the grey areas, despite the algorithm stabilizing the system. As the system approaches its steady state after the disturbance, the system becomes input-output stable with the chosen PID parameters.

as the system is far away from its steady state for which stability is evaluated. However, as the system's output gets close to the set point, i.e. the steady state, the closed loop transfer function becomes stable. Knowing about the relationship between chosen parameters and stability allows to include this knowledge into the training. When used as a regularization term, the parameters for the PID controller could be driven towards stable solutions. Furthermore, the input-output stability evaluation is an important insight for control engineers and makes the neural PID controllers understandable for humans, thus emphasizing its applicability for safety critical systems.

5 Conclusion

In this paper, we conduct an extensive and rigorous investigation into the use of general dynamic neural networks for online PID parameter adaption. We perform experiments on four different systems, with and without sensor noise as well as with and without disturbance, resulting in 16 experiments in total. These scenarios cover the most important challenges in control engineering. This study is therefore unique in its extensiveness. The neural-network-based approach outperforms a standard PID controller in 15 of 16 scenarios and outperforms a model-based controller in 13 of 16 scenarios. These results showcase the potential of extending existing systems by machine learning in general and neural networks in particular. To the best of our knowledge, this is the first investigation that uses general neural networks that include feedback between layers with arbitrary delays, extending the state of the art for using neural networks to tune PID parameters. We perform a detailed analysis for one representative scenario, highlighting the superior control performance of our approach over both the traditional PID controller and model-based backstepping.

Although the significant potential of neural networks for PID parameter tuning is known [6–8], this technique has not been used in real-world applications to date. As the functioning of a neural network in this setting is not understood, control engineers refrain from using them. In a first attempt to solve this problem, we perform a input-output stability analysis to interpret how neural networks function within the suggested framework. Tying the neural network outputs back to stability makes this neural-network-based approach understandable to humans. It is thus an important step to increase the acceptance of machine learning based approaches for real-world systems and is an important step towards explainable and safe applied artificial intelligence.
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