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Improvement of human–machine interface of complex technical systems using fractional-order $PI^{\lambda}D^{\mu}$ controllers

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One of the most essential characteristics of a complex technical system is that it performs 'an important useful function only with the assistance of a human operator and standard infrastructures…' [1]. At the earliest stages of the development of a system, deciding whether the human operator should be regarded as part of the complex system or an external entity is necessary. In most cases, the human operator should be treated as an external entity.

Most complex technical systems cannot function without the active involvement of a human operator, who retains responsibility for decision-making, control, and management functions. From a functional standpoint, operators can be considered an integral part of the system. However, the system designer rarely possesses sufficient authority over the operator to incorporate them fully into the system's design. From the perspective of the systems engineer, the human operator instead represents an element of the system's environment.

Under this paradigm, the systems engineer must devote particular attention to the design and development of the operator interface, which is a critically important aspect of any complex technical system [2]. Accordingly, the development of universal technical solutions that enhance the quality of the human–machine interface in complex technical systems represents both a significant and timely challenge, the resolution of which can be applied across a wide range of practical applications.

The primary objective of the present work is to improve the performance of the human–machine interface by compensating for the inertial and nonlinear characteristics of the human operator as a control element within a complex technical system.

Keywords: inertial and nonlinear characteristics of the human operator, fractional-order $PI^{\lambda}D^{\mu}$ controllers, complex technical system

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INTRODUCTION

According to [1], one of the most essential characteristics of a complex technical system is that it performs 'an important useful function only with the assistance of a human operator and standard infrastructures...'

Choosing whether the human operator should be regarded as part of the complex system or an external entity is necessary at the earliest stages of the development of a system. In most cases, the human operator should be treated as an external entity.

The majority of complex technical systems cannot function without the active involvement of a human operator, who remains responsible for decision-making, supervisory, and control functions. From a functional perspective, the operator may be reasonably regarded as an integral part of the system.

However, the system designer rarely has sufficient authority over the operator to incorporate them fully into the system architecture. From the systems engineer's standpoint, the human operator should therefore be considered an element of the system's external environment.

Under this approach, the systems engineer must devote particular attention to the design and development of the operator interface, which is an essential component of any complex technical system [2].

Accordingly, developing universal technical solutions to improve the quality of the human–machine interface in complex technical systems constitutes a highly relevant and essential engineering challenge. Solving this problem can lead to applicable improvements across various practical domains.

The primary objective of the present study is to enhance the performance of the human–machine interface by compensating for the inertial and nonlinear characteristics of the human operator as a control element within a complex technical system.

LITERATURE REVIEW

The focus in [3] is on the human operator as a source of error, intending to reduce or eliminate those errors and thereby increase the reliability of human-machine systems. The study employs both qualitative and quantitative methods to identify operator errors and the task contexts in which they occur. Quantitative estimates of human error probability are grounded in a qualitative assessment of human factors and task context to ensure that human reliability analysis objectively appraises operator behaviour. They are then refined using the relevant performance-shaping factors.

According to [4], within the Industry 4.0 paradigm, investigating human-machine interaction dynamics and their impact on production performance is a key research issue. The Operator 4.0 concept – an operator integrated into a cyber-physical system – calls for an in-depth human reliability analysis, specifically assessing human error probability (HEP) that takes complete account of the workplace environment. It is noted that HEP is influenced by several psychomotor attributes of operator behaviour, including reaction latency, goal-dependent performance characteristics, the non-stationarity of those characteristics, their pronounced non-linearity, and stochastic nature.

According to [5], employees can damage a company through human error, and such errors are closely correlated with the operator's reliability level: low reliability leads directly to defects in finished products. The study is a descriptive, qualitative investigation that applies the Human Error Assessment and Reduction Technique (HEART) to determine operator reliability.

Reference [6] provides a systematic review of gesture-recognition and motion-capture technologies. It explores how gesture data can be used for ergonomic assessment and control strategies in complex equipment based on operator gesture and motion identification. An optimisation algorithm is developed to obtain the best solution by minimising an objective function that combines the RULA ergonomic score with the cycle time of each assembly workstation, while accounting for individual worker capabilities.

Reference [7] examines the simple psychophysiological visual-motor response (SPPR) latency as a function of waiting time, the interval between the preceding response, and the subsequent stimulus. The resulting monotonic relationship is fitted with an ordinal approximation, and the latency was shown to comprise at least two distinct components.

Operator control actions have a complex psychophysiological nature. Two principal components can be distinguished in the operator's response [8, 9]:

- deterministic component – the response produced by a dynamic element that is equivalent to the human operator when the input signal drives it;
- remnant component ('residual') – the difference between the operator's actual input signal and the response predicted by the corresponding linear model.

The statistical properties of this component are strongly influenced by the nature of the input signal, task complexity, and the ergonomic conditions of a workstation (including operator fatigue), and they can vary substantially over time. However, the referenced studies do not provide any numerical characterisation of the operator's dynamic model.

The mathematical model of an operator in an erratic (human–machine) system must incorporate the full spectrum of human-specific biochemical, physical, and psychophysiological factors. Data obtained from experimental studies can be used to identify this model structurally and parametrically.

Numerous empirical coefficients that can vary across a wide range are present in such models, and the need to identify them from psychophysiological measurements constitutes a demanding scientific and engineering problem.

The contemporary scientific literature describes a variety of approaches to the problem of identifying a mathematical model of the human operator.

One of the most widely used – though by no means the only – approaches to dynamic identification problems in control systems is application of the proven algorithms available in MathWorks System Identification Toolbox® [10].

The distinctive features of operator modelling based on C*-algebras are examined in [11].

The parameter-identification problem for Volterra nonlinear dynamic systems affected by moving-average noise are tackled in [12]. To accelerate convergence, the authors propose a gradient iterative algorithm that replaces unmeasurable variables with their current iterative estimates and refines the parallel noise estimates based on the updated parameter values.

A maximum-likelihood estimation algorithm for nonlinear controlled autoregressive systems of the Hammerstein type with moving-average dynamics (CARARMA), implemented via an iterative Newton method, is proposed in [13].

The effectiveness of modified meta-heuristic algorithms in identifying structural dynamic systems is compared in [14]. The study evaluates a genetic algorithm, an ant-colony optimisation algorithm, and an artificial-bee-colony algorithm, some of which belong to the evolutionary algorithm class and others to the swarm algorithm class. Simulation results demonstrate that the proposed algorithms deliver accurate parameter estimates even with limited measurement data and high noise levels.

The initial release of the MATLAB Non-Parametric System Identification Toolbox is presented in [15]. The toolkit incorporates classical non-parametric techniques (based on kernel methods or orthogonal expansions) and state-of-the-art algorithms, including hybrid approaches that combine parametric and non-parametric identification. The package supports Hammerstein and Wiener models, along with their cascade configurations.

In [16], the System Identification Toolbox® (SIT) is employed to perform parametric identification of a human-pilot behavioural model while flying an X-Plane flight simulator.

The SIT® is used in [17] to obtain a mathematical model of a loss-in-weight feeder employed in cement manufacturing.

The current scientific and engineering literature actively explores the identification of technical systems and the design of control schemes based on dynamic models with fractional order derivatives.

A set of computational routines for working with fractional-order transfer functions in MATLAB is introduced in [18].

Reference [19] gives a detailed description and illustrative examples of the FOMCON library, which automates the dynamic identification of plants via fractional-order transfer functions and enables the synthesis of fractional-order $PI^{\lambda}D^{\mu}$ controllers for dynamic systems.

References [20, 21] likewise report successful identification and control of technical objects using fractional-order transfer functions. To date, however, this approach has not been applied to the dynamic identification of the human operator.

THE AIM AND OBJECTIVES OF THE STUDY

This study aims to develop a compensator architecture that mitigates the human operator's inertial and nonlinear characteristics by employing a fractional-order $PI^{\lambda}D^{\mu}$ controller and to determine how this compensator affects the control quality metrics of a complex technical system.

The following tasks were defined to achieve the objective

1. Conduct an experimental investigation of the human operator's physiological response while acting as a control element within a complex technical system.
2. Dynamically identify the human operator and select an appropriate representation for the operator's transfer function.
3. Synthesise a fractional-order $PI^{\lambda}D^{\mu}$ controller tailored to the identified operator model.
4. Analyse the dynamic performance of the complex system when governed by the controller and evaluate the resulting control quality indices.

RESEARCH MATERIALS

Experimental study: setup and results

An experimental investigation was carried out to develop a model of operator responses. Twenty subjects participated in the experiment, where, within the MATLAB/Simulink model created by the authors (Fig. 1), they used a joystick to track a step-input reference signal. The amplitude and the onset time of each step were assigned at random. The subjects displayed diverse psychomotor characteristics; each completed five trials, for a total of 100 trials.

During the experiments, Logitech Extreme 3D Pro L942-000031 and Radiomaster TX12 joysticks were used (Fig. 2).

Fig. 2. External appearance of the joysticks used in the experimental study: a – Logitech Extreme 3D Pro L942-000031; b – Radiomaster TX12

The operator's actions were stored in a dedicated variable in the MATLAB Workspace. Figure 3 shows representative operator performance while tracking a step reference signal in the developed model.

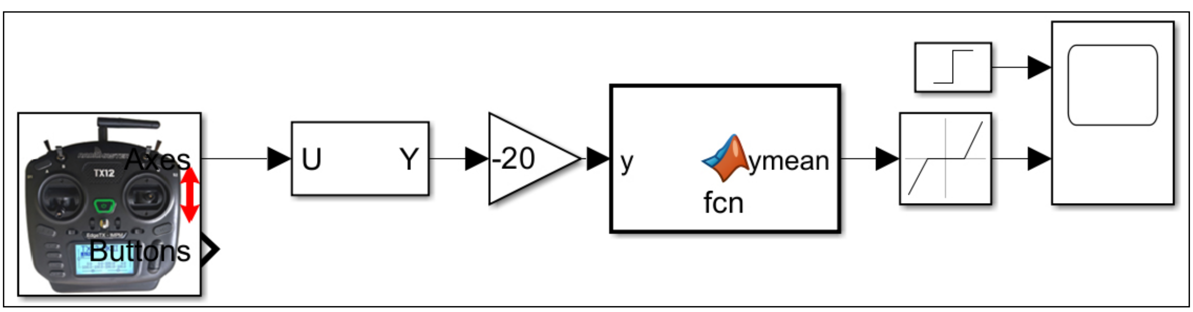


Fig. 1. MATLAB/Simulink model used for the experimental study

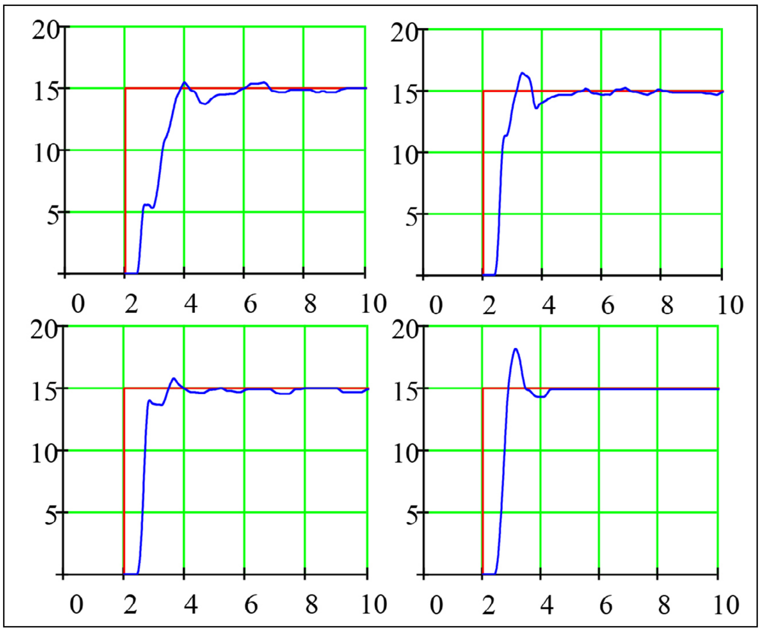


Fig. 3. Examples of the operator participants' performance during the experiment

An operator-response model can be derived in two ways: by averaging the identification parameters of each response curve or by first averaging the response curves themselves and then identifying the parameters of the resulting mean curve.

Next, we will carry out an analytical and mathematical comparison of these parameter-identification methods.

Assuming that we have a set N of dynamic response curves $y_i(t)$, each is described by the same parametric model:

$$y_i(t) = f(t, \theta_i) + \varepsilon_i(t), i = 1, 2, \ldots, N \tag{1}$$

where: $f(t, \theta_i)$ is the parametric response-curve model with parameter vector θ_i, and $\varepsilon_i(t)$ represents random noise.

Let us determine the parameters that best characterise the overall behaviour of the system.

Approach 1: averaging the identification parameters of the individual curves.

For each curve $y_i(t)$ we separately identify its parameter vector $\hat{\theta}_i$:

$$\hat{\theta}_i = arg \min_{\theta} \sum_t \left(y_i(t) - f(t,\theta)\right)^2. \tag{2}$$

Then the average parameter vector is:

$$\bar{\theta} = \frac{1}{N} \sum_{i=1}^{N} \hat{\theta}_i. \tag{3}$$

The model based on the averaged parameters takes the form:

$$\hat{y}(t) = f(t, \bar{\theta}) \tag{4}$$

This approach is straightforward to implement; however, the variance of the parameter estimates can be significant when the individual curves display substantial variability, and in the nonlinear-model case, the mean parameter vector $\bar{\theta}$ does not necessarily minimise the average fitting error.

Approach 2: identification of parameters from the averaged response curve

First, all measured curves are averaged:

$$\bar{y}(t) = \frac{1}{N} \sum_{i=1}^{N} y_i(t). \tag{5}$$

We then identify the parameter vector $\hat{\theta}_{eq}$ for the averaged curve:

$$\hat{\theta}_{eq} = arg \min_{q} \sum_t \left(\bar{y}(t) - f(t,\theta)\right)^2. \tag{6}$$

The resulting model is:

$$\hat{y}_{eq}\left(t\right) = f\left(t, \hat{\theta}_{eq}\right). \tag{7}$$

Applying the curve-averaging approach reduces the influence of random noise, because the noise is averaged out and yields more stable parameter estimates. In nonlinear systems, however, the parameters identified from the averaged curve can differ significantly from the averaged parameters of the individual curves.

The mean equivalent curve is shown in Fig. 4.

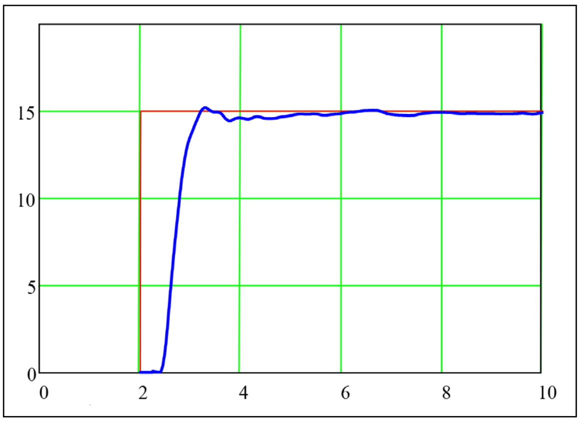


Fig. 4. Averaged equivalent operator response curve

In summary, averaging the response curves reduces random errors. It provides more stable results, while identifying the parameters of the averaged curve is preferable because it minimises the mean fitting error. By contrast, averaging the parameters can introduce systematic errors, since the mean parameter values fail to capture nonlinear effects. This distinction is essential for nonlinear models, in which direct parameter averaging can yield incorrect results.

Identification of the characteristics of the human operator using an integer-order transfer function

A comparative analysis was conducted to determine how closely the transient responses of various candidate transfer-function types matched the experimental data presented above for the structural and parametric identification of the human-operator transfer function. The integer-order transfer functions considered in this study are listed in Table 1.

To perform the structural and parametric identification of the operator's dynamic model, the built-in process routine from MATLAB's System Identification Toolbox® was employed.

The regression coefficients obtained for the various candidate models are listed in Table 1.

As the data show, all models achieve a very high regression coefficient (exceeding 95%). Consequently, for further analysis, it is sufficient to adopt the simplest candidate: the first-order-plus-dead-time (P1D) dynamic model.

The parameter estimates for the P1D human operator model are summarised in Table 2.

Thus, based on the experimental study, it was established that the human operator transfer function could be represented in the following form:

Table 1. **Integer-order transfer functions investigated for modelling the human operator**

No.	Model name	Model transfer function	Regression coefficient
1	P1D	$G(s) = \dfrac{K_P}{1 + T_{P1}S} e^{-T_d \circ s}$	96.60%
2	P2DU	$G(s) = \dfrac{K_P}{1 + 2\xi T_W s + (T_W s)} e^{-T_d s}$	97.30%
3	P3DU	$G(s) = \dfrac{K_P}{1 + 2\xi T_W s + (T_W s)^2) \cdot (1 + T_{P3} s)} \cdot e^{-T_d s}$	97.30%
4	P1DZ	$G(s) = \dfrac{K_P (1 + T_Z s)}{1 + T_{P1} s} e^{-T_d s}$	96.50%

Table 2. **Parameter-identification results for the P1D operator model**

Parameters of transfer function P1D	Mean value, μ	Standard deviation, σ
K_P	1.004	0.0098
T_{P1}	0.25349	0.14967
T_D	0.57644	0.15444
R, %	92.62	6.0382

$$G_S(s)=\frac{K_P}{1+T_{P1}s}e^{-T_d s}=$$
$$=\frac{1}{0.25349s+1}\cdot e^{-0.57644s} \qquad (8)$$

Identification of the characteristics of the human operator using a fractional-order transfer function

To identify the operator with a fractional order transfer function, we employed the FOMCON library for MATLAB, which implements the fractional order integral via the Oustaloup recursive approximation, realised as a cascade of first-order integrator–differentiator elements [22].

Below, we set out the step-by-step procedure for identifying the operator's fractional-order transfer function using the averaged response curve.

First, create an FIDATA variable named operator by calling the fidata function as follows:

operator = fidata(y, u, t);

To initiate the fractional-order identification procedure, enter the command fotfid in the MATLAB Command Window; this launches the dedicated FOMCON tool (Fig. 5).

After the fractional order identification is complete, it is recommended that a variable that stores the identification parameters be saved to the Workspace (Fig. 6).

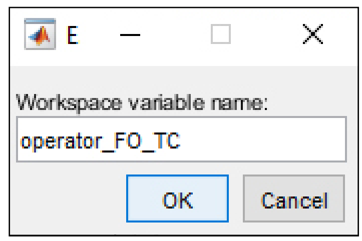


Fig. 6. Saving the fractional-order identification results to a Workspace variable

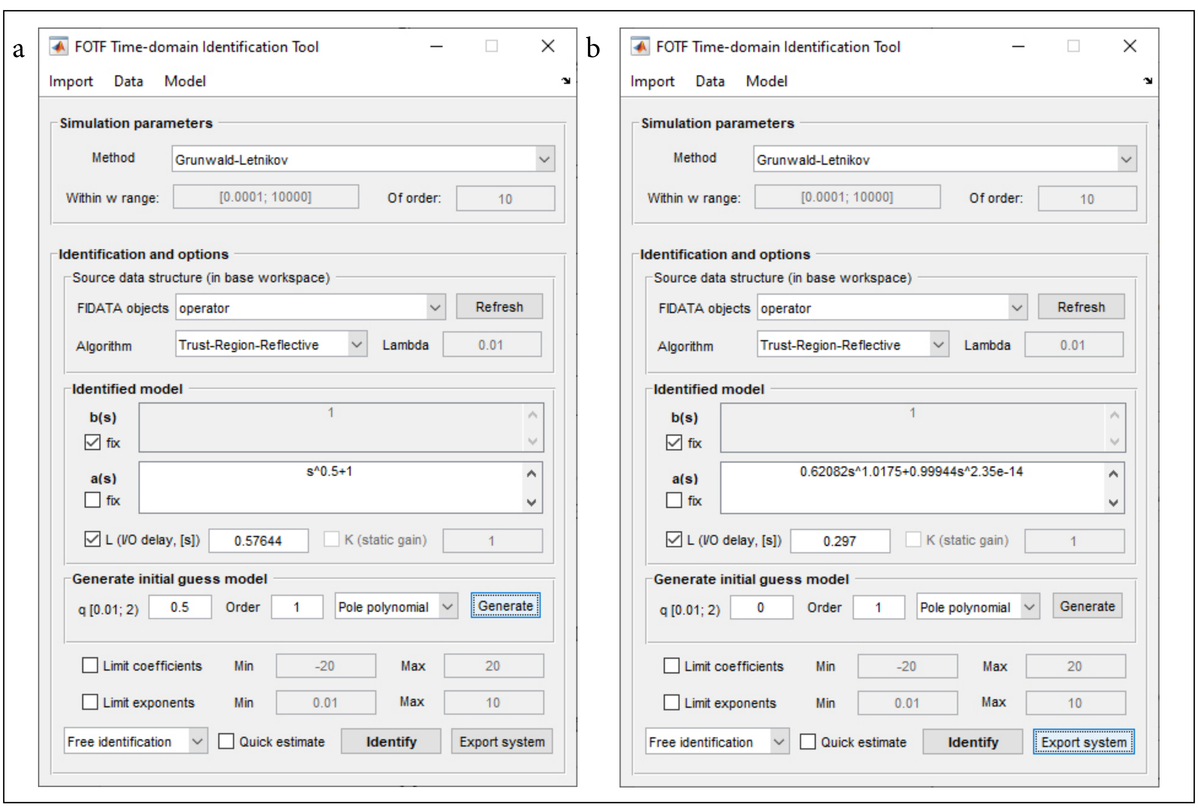


Fig. 5. Using the FOMCON fotfid tool for fractional order dynamic identification: a – setup; b – identification result

It is recommended to round the obtained results to avoid calculation inaccuracies and the appearance of coefficients comparable to machine zero:

round(operator_FO_TC, 1e-4, 1e-4)

To assess the quality of the obtained model, execute the following command:

validate(operator, operator_FO_TC)

The result of executing this command is presented in Fig. 7.

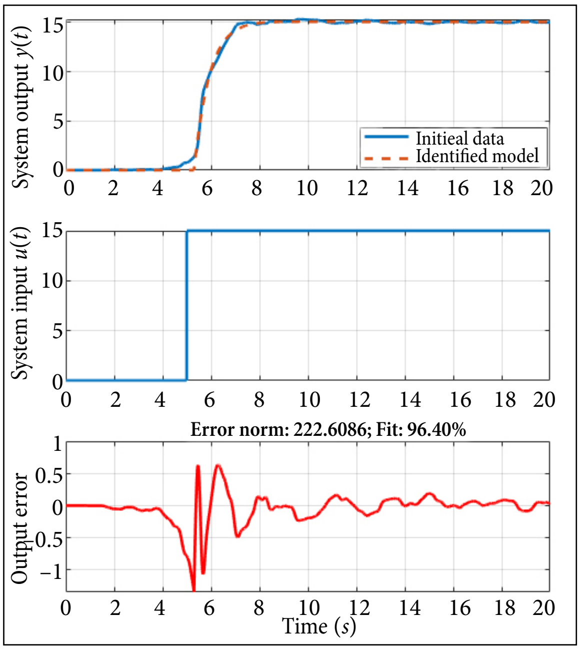


Fig. 7. Quality assessment of the human operator fractional order transfer function

One of the outputs of the validate command is the regression (fit) coefficient of the identified model.

We shall represent the operator's fractional-order transfer function in the following general form:

$$F_1(s) = \frac{1}{T_{P1}s^{\alpha} + 1}. \quad (9)$$

The acronym FOP1 (Fractional Order Poles = 1) was adopted for this transfer function form.

The statistical results of the parameter estimation for the FOP1 fractional-order human operator transfer function are summarised in Table 3.

Table 3. **Parameter identification results for the FOP1 fractional order human operator transfer function**

No.	Parameter	Mean value, μ	Standard deviation, σ
1	T_{P1}	0.90718	0.21631
2	α	1.1782	0.04322
3	R	83.2591	5.1704

Table 3 shows that the mean regression coefficient R for the FOP1-type fractional-order human operator transfer function is roughly 83%; only one experiment produced an R value below 70%. R for the FOP1 model is noticeably lower than for the integer-order P1D model.

Although the FOP1 model yields a lower regression coefficient than the P1D model, it cannot be discarded – its fit is still high, exceeding 80%.

The P1D model is often a sensible approximation of process behaviour. It has proved helpful for controller-tuning rules, structuring decoupling devices and feedback algorithms, conveying key process characteristics, and being a lightweight surrogate in training and optimisation simulators.

Nevertheless, P1D is not necessarily a faithful representation of the actual process. It is a practical compromise that balances several aspects of usefulness.

The process is likely to be more complex. For example, Fig. 4 shows a prolonged 'creep' toward steady state at the end of the transient, a feature typical of systems governed by fractional-order differential equations.

Therefore, the present study focuses on identifying the human operator transfer function with fractional-order models of the FOP1 type rather than their linear P1D counterparts. Although the FOP1 model yields a lower mean regression coefficient, it is more likely to represent the operator's dynamics accurately.

A further reason to favour an FOP1 operator model is the relative ease of designing control systems for such a plant, because its structure contains no explicit transport delay element.

Application of controllers in the human–machine interface of complex technical systems

The principal difficulty in a human–machine interface in a complex system is that, regardless of the operator's skill level, the human introduces additional distortions into the control signals applied to the system's actuating inputs, as illustrated in Fig. 4. One of the theoretically simplest and technically most accessible ways to improve control quality is to incorporate an auxiliary controller directly into the interface, thereby partially compensating for the operator's non-linearity and inertia (Fig. 8).

A key advantage of this approach is that the compensating controller becomes an integral part of the overall system, and its design is governed solely by the operator's characteristics, independent of the plant dynamics.

Theoretically, the operator's non-linearity and inertia compensation could be achieved by cascading a corrective element whose transfer function is the exact inverse of the human operator's transfer function.

In practice, such a solution is unattainable, because (1) the precise form of the operator's transfer function is still an open research problem, and (2) the operator's psychophysiological state – and hence the parameters of that transfer function – can vary over a wide range.

Using the identification results obtained above, we now demonstrate how a controller can mitigate the operator's physiological response for the integer order transfer function (8) and the fractional-order transfer function (9).

Accordingly, two realisations of the corrective element are proposed, featuring integer and fractional order transfer functions, respectively.

$$W_{C\_IO}(s) = \frac{(T_{P1} + T_d)s + 1}{T_\mu s + 1} = \frac{0.83s + 1}{0.05s + 1}$$

$$W_{C\_FO}(s) = \frac{T_{P1}s^\alpha + 1}{T_\mu s + 1} = \frac{0.90718s^{1.1782} + 1}{0.05s + 1}, \quad (10)$$

where $T\mu$ is a small time constant required to ensure the proper operation of the differentiating elements.

Investigation of controllers of various types for compensating human operator characteristics in a mathematical model

The following experimental plan was devised to examine the performance of different controller types.

Assuming there is an ideal reference control signal Uref(t). The operator's actions, transmitted through the available control devices, distort this signal, producing Ujoy(t). This distorted signal is applied to the controller input, which generates a corrected control signal Ucor(t) at its output; Ucor(t) is then fed to the plant input. The plant executes the control command and produces the output trajectory Uout(t).

In the ideal case, with neither a human operator nor an auxiliary controller present, the system yields an idealised plant trajectory. This perfect response will later serve as a benchmark for evaluating the quality of the compensating device.

To improve the reliability of the results, a periodic reference signal Uref(t) in the form of a meander (square wave), with a period of 10 s and a 50% duty cycle.

The signal's total duration is 360 s, and its amplitude varies between 0.4 and 0.9.

The reference signal Uref(t) is processed by the human operator, who inevitably introduces

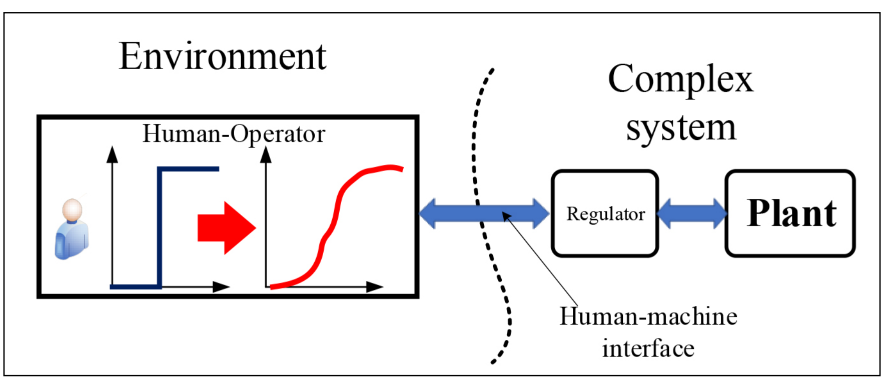


Fig. 8. The principle of using controllers to compensate for the human operator

distortions, at least due to delays in physiological response. The plots of the operator's response Ujoy(t), averaged over all periods and overlaid with the reference control signal Uref(t), are shown in Fig. 9.

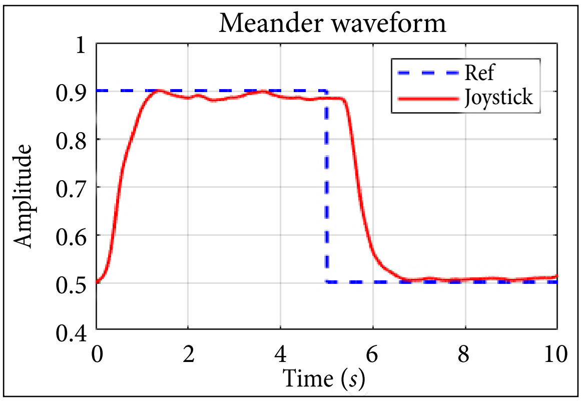


Fig. 9. Control signal Uref(t) and the averaged human operator response Ujoy(t) used in the study

Two alternative plants were analysed as the control object:

1. Plant DA – the model structure is first-order plus dead time (FOPDT) with the transfer function

$$G(s) = \frac{1}{1+s}e^{-s}. \qquad (11)$$

2. Control plant DCM – a standard DC-motor model with the following parameters: rated power 1750 kW; armature voltage 600 V; rotational speed 190 rpm; armature resistance 0.0326 Ω; armature inductance 0.000651 H; flux constant 25.13 V·s; moment of inertia 18 000 kg·m^2.

The plant responses will be analysed to evaluate the influence of operator dynamics while the operator's equivalent time constant is varied within ±50% of the nominal value obtained from Tables 2 and 3.

During each experiment, the plant's response to the signal Ujoy(t) was computed for different variants of the compensating element. An averaged plant response over one period of the control signal was obtained for every experiment.

To evaluate the quality of the various controllers, the plant response obtained with the compensator must be compared with the plant response to the ideal control signal Uref(t).

Several criteria can be used to assess the similarity of two data arrays of equal length:

1. Pearson correlation coefficient

This metric quantifies the linear dependence between the arrays; a coefficient value close to 1 indicates high similarity in data trends.

2. Mean-squared error (MSE)

Computed as the average of the squared differences between corresponding elements of the arrays; the smaller the MSE, the closer the arrays are in absolute value.

3. Cosine similarity

Evaluates the angle between the vectors formed from the arrays; a value close to 1 indicates that the vectors point in almost the same direction, signalling similarity in their structure.

These criteria capture the absolute similarity of the values, their relative alignment, and inter-relationship.

In the present study, the mean-squared error (MSE) is adopted as the evaluation metric.

The consolidated results of the investigation are presented in Fig. 10.

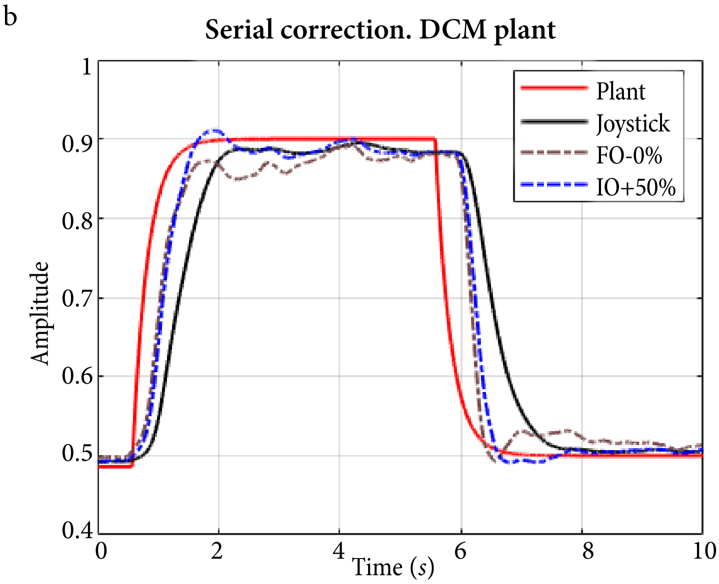
The tables embedded in Fig. 9 list the MSE values obtained by comparing the plant response in the operator-in-the-loop configuration with the benchmark response of the uncontrolled plant. The following labels are used: Joy – operator without a controller; f00 – operator with a fractional-order controller, time constant T_{P1}; f05 – operator with a fractional-order controller, time constant 0.5 × T_{P1}; f15 – operator with a fractional-order controller, time constant 1.5 × T_{P1}; i00 – operator with an integer-order controller, time constant T_{P1}; i05 – operator with an integer-order controller, time constant 0.5 × T_{P1}; i15 – operator with an integer-order controller, tim constant 1.5 × T_{P1}.

Analysis of the MSE values shows that a compensator tuned with the nominal time constant T_{P1} effectively offsets the operator's influence on the plant for both integer- and fractional-order designs. Overall, the fractional-order $PI^{\lambda}D^{\mu}$ controller is preferable, as it provides the highest level of compensation for human-operator effects.

a

Corrector	MSE
{'Joy'}	0.011123
{'fo00'}	0.0067114
{'fo05'}	0.0047427
{'fo15'}	0.014314
{'io00'}	0.0056021
{'io05'}	0.0054832
{'io15'}	0.010395

b



c

Corrector	MSE
{'Joy'}	19.154
{'fo00'}	11.397
{'fo05'}	13.745
{'fo15'}	11.399
{'io00'}	11.652
{'io05'}	14.26
{'io15'}	10.866

d

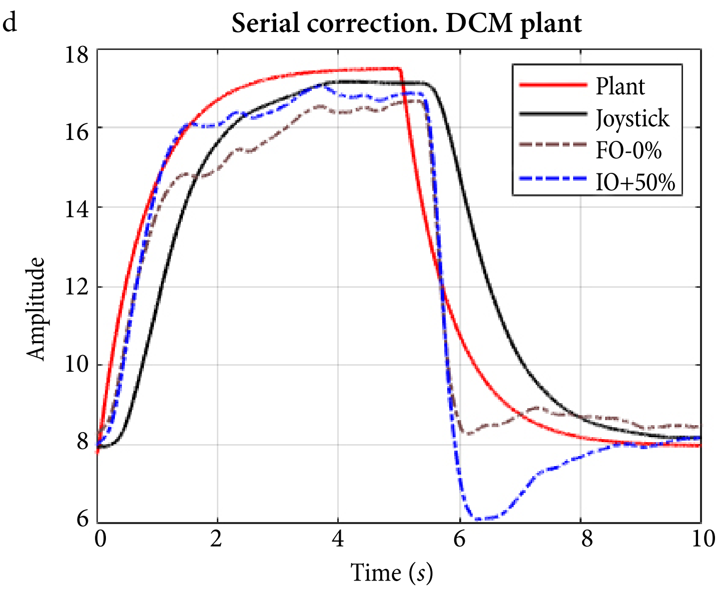


Fig. 10. Comparison of the plant response without a controller and with controllers of various types

CONCLUSIONS

The principal outcome of this study is an improvement in the quality of the human–machine interface of complex technical systems by compensating for the operator's inertial and nonlinear physiological response through the use of fractional-order $PI^{\lambda}D^{\mu}$ controllers.

The experiments showed that a simplified, classical integer-order model with dead time (P1D) provides highly accurate dynamic identification of the operator, with a regression coefficient of 92.6%. Although the fractional-order model (FOP1) yields a somewhat lower average regression coefficient (≈83%), it better captures additional features of operator dynamics, such as remnant effects and parameter variations linked to physiological state. Furthermore, identification and transient-response calculations performed with the FOMCON toolbox demonstrate that software implementation of fractional-order controllers, based on the Oustaloup decomposition, into a finite set of first-order integrator–differentiator blocks is readily executable on modern microcontrollers and computers.

The study validated the controllers on two plants – a first-order process with dead time and a second-order process. Controller effectiveness was measured by the mean-squared deviation of the plant output from a benchmark trajectory in which the human operator's influence was entirely removed. The results show that the controllers reduce this deviation by 60%.

These findings confirm that fractional-order $PI^{\lambda}D^{\mu}$ controllers can compensate the operator's inertia and nonlinearity, enhancing human–machine interface performance in complex systems. They lay the groundwork for further research into optimised human–machine interaction and open the way to adaptive identification methods and real-world industrial deployment of the proposed controllers.

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SUDĖTINGŲ TECHNINIŲ SISTEMŲ ŽMOGAUS IR MAŠINOS SĄSAJOS TOBULINIMAS NAUDOJANT TRUPMENINĖS EILĖS $PI^{\lambda}D^{\mu}$ REGULIATORIŲ

Santrauka

Viena svarbiausių sudėtingos techninės sistemos savybių yra ta, kad ji „atlieka svarbią naudingą funkciją tik dalyvaujant žmogui operatoriui ir naudojant standartinę infrastruktūrą...“ [1]. Ankstyviausiose sistemos kūrimo stadijose būtina nuspręsti, ar žmogus operatorius turėtų būti laikomas sudėtingos sistemos dalimi, ar išoriniu subjektu. Daugeliu atvejų žmogus operatorius turėtų būti laikomas išoriniu subjektu.

Dauguma sudėtingų techninių sistemų negali veikti be aktyvaus žmogaus operatoriaus dalyvavimo, nes jis išlieka atsakingas už sprendimų priėmimą, kontrolę ir valdymą. Funkciniu požiūriu operatorius gali būti laikomas neatskiriama sistemos dalimi. Tačiau sistemos projektuotojas retai turi pakankamai įgaliojimų operatoriaus atžvilgiu, kad galėtų jį visiškai įtraukti į sistemos projektą. Iš sistemos inžinieriaus perspektyvos žmogus operatorius vertinamas kaip sistemos aplinkos elementas.

Pagal šią paradigmą, sistemų inžinierius turi skirti ypatingą dėmesį operatoriaus sąsajos projektavimui ir kūrimui, nes tai yra vienas svarbiausių bet kurios sudėtingos techninės sistemos aspektų [2]. Todėl universalių techninių sprendimų, gerinančių žmogaus ir mašinos sąsajos kokybę sudėtingose techninėse sistemose, kūrimas yra svarbus ir aktualus uždavinys, kurio rezultatai gali būti pritaikomi įvairiose praktinėse srityse.

Pagrindinis šio darbo tikslas – pagerinti žmogaus ir mašinos sąsajos veikimą, kompensuojant žmogaus operatoriaus, kaip sudėtingos techninės sistemos valdymo elemento, inercines ir netiesines charakteristikas.

Reikšminiai žodžiai: žmogaus operatoriaus inercinės ir netiesinės charakteristikos, trupmeninės eilės $PI^{\lambda}D^{\mu}$ reguliatoriai, sudėtinga techninė sistema