Modelling, simulation and real-time control of a laboratory tide generation system

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1. Introduction

Small-scale experiments allow us to reproduce and understand phenomena and to draw inferences about large-scale processes, especially when factors that intervene can be hardly controlled. The particular process we are interested in is the morphological evolution of lagoonal environments and, to reproduce this phenomenon in scale, we have designed a peculiar experimental apparatus (Stefanon, Carniello, D’Alpaos, & Lanzoni, 2010). To understand some technical choices and purposes of the experiment, it may be helpful to briefly report the main characteristics of the natural process.

Tidal systems are fragile and complex environments based on a delicate balance between a variety of drivers, such as sediment transport, geology, hydrodynamics, vegetation and human actions (Coco et al., 2013). Understanding the main processes that underlie the formation and development of tidal networks is necessary to address issues of conservation of these habitats, exposed to the effects of climate changes and human interference. In a tidal system the primary external hydrodynamic forcing is represented by the tide. The greatest difference between tidal networks and their fluvial counterpart is that they are forced by a bidirectional flux. Indeed, the velocity is direct towards the land during the flood and towards the sea during the ebb. As a result, sediments are transported in different direction during these phases, and morphology is shaped according to this actions of erosion and deposition. Moreover, the morphology itself modifies the nature of the flux, because velocity increases in channels and decreases over vegetated shallow areas. Therefore a difference between the velocity can be experienced during the two phases of the tide and influence the morphology of a tidal environment (Fig. 1a). This difference is referred as tidal asymmetry and can be described using the ratio $p_s$ between the flood peak and the ebb peak of the cross-sectionally averaged velocity. This parameter provides a distinction of the asymmetrical tidal flow into flood dominated ($p_s > 1$) and ebb dominated ($p_s < 1$). This characteristic of the flow can be easily visualized in the velocity-stage plot (Fig. 1b): an ellipse represents a symmetric tide, while increasing asymmetry produces distorted shapes. What is more, according to Tambroni, Luchi, and Seminara (2017), the nature of the flow field (i.e. flood or ebb dominance) is strictly related with the morphology of the tidal basin, e.g. the position of the point bars relative to the apex of a meander is strongly affected by the tidal asymmetry (Fig. 2). Once understood that the tide cannot simply be modelled with a symmetrical, sinusoidal wave and that particular waveform influences the morphology of tidal basins, it should be clear that the experimental apparatus has to be able...
The chance to conduct meaningful in-scale experiments relies significantly on the behaviour of the artificial tide, that has to exhibit predefined characteristics. To this aim, the height of the artificial water wave has to be controlled in real-time. To simulate the relevant system dynamics, for a first assessment of the different control strategies, a useful tool is represented by Computer Aided Control Systems Design (CACSD) softwares (Beghi et al., 2017; Chin, 2017). In order to setup a useful simulation-centric control system design project, there is a preliminary step to be taken into account, namely the derivation of a dynamic model (which translates certain interesting properties of the real system into mathematical equations) of the system to be controlled. In order to develop an effective model we need to know the domain expert’s (i.e. the actual knowledge of the process and its properties) and the knowledge engineer’s (i.e. how the process functioning and its properties can be transferred into a useful model) (Ljung & Glad, 1994).

The considered artificial tide generation apparatus is a non-trivial system from a modelling point of view. Basically, it includes a water pump and a vertical sharp-edge weir, which oscillates vertically thanks to a stepper motor. The artificial apparatus represents an example of a multi-domain physical system (electrical, mechanical, and hydraulic). The system exhibits non-linear behaviours with fast dynamics (e.g. the electro-mechanical sub-system) and slow dynamics (the hydraulic sub-system), plus dead time (due to the water mass transport). On the other hand, new technologies provide new opportunities for modelling and simulation. In the first part of this paper, we exploit the potential offered by a hybrid approach that combine the traditional causal (i.e. block-oriented) modelling approach with the acausal (i.e. declarative) one (Kofranek, Matejak, Privitzer, & Tribula, 2008). Beside this, these tools enable physical modelling of multi-domain physical systems. In particular, we have developed a Matlab-based simulation environment for the artificial tide generation system by means of Simulink causal block diagram and Simscape acausal components (Dingyu Xue, 2013; Ramin S. Esfandiari, 2014). The resulting simulation environment represents an useful tool to design the artificial tide generation apparatus control system, to which the second part of this paper is devoted.

The control system should be able to track the reference wave signal (e.g. with fixed amplitude, period, and mean level of propagation), guaranteeing suitable performance (i.e. stability, robustness, and time-domain performance). In particular, the system should reproduce asymmetrical tides to study the effects on the morphological development of a lagoonal environment.

As previously mentioned, the system exhibits non-linear behaviours and, moreover, it is expected that certain system configurations and boundary conditions change during new campaigns of experiments. In this scenario, traditional model-based control approach may be difficult to use since it is non-trivial to develop and calibrate an effective system dynamic model. Beside these aspects, we must mention that the control algorithm has to be designed under some technological constraints, given by the fact that it has to be implemented as an upgrade of a traditional control unit with limited computational and memory resources.

For these reasons, we want to develop a control algorithm as simple as possible but able to ensure suitable performance, even when the system operating conditions change or if certain system parameters vary over time, avoiding tedious and time-consuming controller retuning. Specifically, we want to exploit the intelligent Proportional–Integral–Derivative (i-PID), that is a step towards a model-free control of plants with completely or partially unknown dynamics (Fliess & Join, 2009, 2013). The i-PID strategy combines a feed-forward control based on the identification of local models (which represent the plant dynamics over short periods of time) with conventional PID algorithms. In particular, an i-PI controller is developed and implemented on real hardware. The experimental results show the good performance of the i-PI controller which results appropriate to drive the artificial tide generation.

The paper is organized as follows. In Section 2, the experimental apparatus is depicted. Section 3 is devoted to the system modelling,
Fig. 3. Experimental set-up.

To reproduce a typical lagoonal environment we have used a large indoor apparatus, schematically depicted in Fig. 3, which is composed by two adjoining basins representing the sea and a back-barrier lagoon (Fig. 3a, the plant view and Fig. 3b a section).

The lagoon basin is 5.3 m long and 4.0 m wide, while the much deeper adjacent sea basin is 1.6 m long and 4.0 m wide. The sea is separated from the lagoon by a barrier of wooden panels, which can be moved to create inlet with different shape and position and a shelf enable us to represent the gentle slope of the sea bed in front of the lagoon. During the experiments, the lagoon is covered with a layer of sediments made of cohesionless plastic grains (Fig. 3c). The tide is generated at the sea by the combined action of a pump and a vertical sharp-edge weir, which is moved by a stepper motor and oscillates vertically. The water continuously flowing over the weir is collected in a separate tank, where the pump recirculates the flow (Fig. 3d). The apparatus is equipped with two ultrasonic probes that provide a measurement of the water level in the sea, a potentiometer to measure the position of the weir and a computer driven pantograph to survey the bed elevation within the lagoon. It is worth highlighting that, the wave generated at the weir does not maintain its form (i.e. it reduces the amplitude and experiences a time delay) during the propagation to the lagoonal inlet, because of inertia. This is the reason why the tidal wave cannot be imposed in the section of the weir but should be reproduced in front of the lagoon to be sure of the characteristic of the wave.

A block diagram of the system is depicted in Fig. 4. In broad terms, the system can be outlined as two sub-systems that interact with each other in a structured manner:

- the electro-mechanical sub-system, which includes: the driver, the stepper motor, the worm gear, the lead-screw, and the sharp-edge weir;
- the hydraulic sub-system, which includes: the water, the sea, the shelf, the lagoon, and the water pump.

In order to conduct meaningful in-scale experiments, which relies significantly on the characteristics of tide, the water level at the sea is controlled by manipulating the stepper motor position, which in turn, determines the sharp-edge weir height position, while the water pump is set to a fixed flow rate.

3. Modelling

To preliminary assess different control algorithms, we design a model-based simulation environment for the artificial tide generation system. It is a common practice to build a mathematical model of a complex system like the considered experimental apparatus by aggregating sub-models of its constituent parts, i.e. by using a modular modelling approach. From this point of view, two options are generally available: causal (or procedural) approach and acausal (or declarative) one. It is worth highlighting that, the causality can explain the evolution which was in the past declared as the evolution from block oriented tools into object oriented tools.

In the first approach, one assumes that a system can be decomposed into block diagram structures with causal interactions, the model is described in a form which is close to the numerical solution algorithm and the interaction between the models is formalized in terms of input and output variables. In this way, it is rather straightforward to simulate elementary and aggregate models. On the other hand, a significant effort in terms of analysis and analytical transformations is often needed to obtain this system form (e.g. the equations would be converted to ordinary differential equations, ODEs, form manually). Furthermore, the causal model exhibits low re-usability and the corresponding code may be difficult to read or modified a posteriori. Conversely, in the acausal approach, the model is described by equations in a context-independent form, without caring about the actual solution algorithm. From this point of view, two options are generally available: causal (or procedural) approach and acausal (or declarative) one. It is worth highlighting that, the causality can explain the evolution which was in the past declared as the evolution from block oriented tools into object oriented tools.

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Furthermore, the interaction between the models is formalized in terms of connection equations without any specification on causality. The acausal approach exhibits both high re-usability and high readability of the basic models. On the other hand, it is more difficult to go

and to the model calibration and validation. Examples of simulation are shown in Section 4. Section 5 is dedicated to the design of the i-PI controller. Results corresponding to the use of standard and intelligent control algorithms are presented in Section 6. Some conclusions and remarks are drawn in Section 7.

2. Experimental apparatus

To reproduce a typical lagoonal environment we have used a large indoor apparatus, schematically depicted in Fig. 3, which is composed by two adjoining basins representing the sea and a back-barrier lagoon (Fig. 3a, the plant view and Fig. 3b a section).
from the mathematical model to the numerical simulation algorithm. It is worth highlighting that, each of the aforementioned approaches has its intrinsic advantages and disadvantages. In this application, we want to exploit the advantages provided by both approaches and so a mix of causal and acausal models are used. In particular, we develop a Matlab-based simulation environment for the artificial tide lagoon generation system by means of Simulink and Simscape components. In traditional Simulink block-oriented tools (causal), the signals are transmitted through links between individual blocks and they serve to transfer values of individual variables from the output of one block to the inputs of other blocks. Input information is processed in the blocks to output information and the interconnection of blocks reflects both the structure of the modelled real system and the calculation procedure (Perelmuter, 2017). Conversely, Simscape lets use and define components as textual files, complete with parametrization, physical connections, using DAEs. In the following, the main physical components of the systems, such as the electro-mechanical sub-system and the hydraulic one are modelled by means of Simscape blocks, while the control systems are modelled by means of traditional Simulink causal blocks.

3.1. Electro-mechanical sub-system

The experimental apparatus is composed by the following main electro-mechanical components: a driver, a stepper motor, a worm gear coupled with a lead-screw, and a sharp edge weir.

By way of an example, we show the dynamic equations (1) that reproduce the behaviour of the electric motor, where $e_A$ and $e_B$ are the back emfs induced in the A and B phase windings, respectively, $i_A$ and $i_B$ are the A and B phase winding currents, $v_A$ and $v_B$ are the A and B phase winding voltages, $K_m$ is the motor torque constant, $N_r$ is the number of teeth on each of the two rotor poles, $R$ is the winding resistance, $L$ is the winding inductance, $R_m$ is the magnetizing resistance, $B$ is the rotational damping, $J$ is the inertia, $\omega$ is the rotor speed, $\theta$ is the rotor angle and $T_d$ is the detent torque amplitude. The main values of the parameters of the stepper motor are shown in Table 1.

$$e_A = -K_m \omega \sin(\theta) + K_m \omega \cos(\theta),$$
$$e_B = -K_m \omega \sin(\theta - \pi),$$
$$\frac{di_A}{dt} = \frac{v_A}{L} - \frac{R}{L}i_A - \frac{e_A}{L},$$
$$\frac{di_B}{dt} = \frac{v_B}{L} - \frac{R}{L}i_B - \frac{e_B}{L},$$
$$T_s = J \frac{d\omega}{dt} + B \omega,$$  
$$T_s = -K_m(i_A - \frac{e_A}{R_m})\sin(N_{r}\theta)$$
$$+ K_m(i_A - \frac{e_A}{R_m})\cos(N_{r}\theta) - T_d \sin(4N_{r}\theta),$$
$$\frac{d\theta}{dt} = \omega.$$

Table 1 - Main parameters of the stepper motor.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum supply voltage</td>
<td>230</td>
<td>V</td>
</tr>
<tr>
<td>Motor phase current</td>
<td>2</td>
<td>A</td>
</tr>
<tr>
<td>Nominal torque</td>
<td>4</td>
<td>Nm</td>
</tr>
<tr>
<td>Rotor inertia</td>
<td>2.2</td>
<td>kg cm$^2$</td>
</tr>
<tr>
<td>Step per revolution</td>
<td>200</td>
<td>step</td>
</tr>
<tr>
<td>Winding resistance</td>
<td>1.8</td>
<td></td>
</tr>
<tr>
<td>Current time rise constant</td>
<td>9</td>
<td>m s</td>
</tr>
</tbody>
</table>

3.2. Hydraulic sub-system

The hydraulic components of the system (Fig. 6) can be described using the equations that govern the underlying physics. The experimental apparatus can be divided into two control volumes: $V_{1i}$, which represents the portion of the sea basin between the weir and the deflector panels, and $V_{2i}$, which includes the lagoon and the remaining portion of the sea basin.

For each of these control volumes, we can write a continuity equation. For $V_{1i}$ it results as follows:

$$A_i \frac{dh_{1i}}{dt} = Q_m - (Q_f + Q_{1f}),$$

where $h_i$ is the water level, $A_i$ is the area of the control volume, $Q_m$ is the pump flow rate, $Q_f$ is the flow rate exchanged with $V_{2i}$, and $Q_{1f}$ is the overflow rate from the weir; whereas, for the control volume $V_{2i}$, the continuity equation results as follows:

$$A_i \frac{dh_{2i}}{dt} = Q_f,$$

where $A_i$ is the sum of the sea basin area and the lagoon basin area and $h_{2i}$ is the water level in this control volume.

We add two equation on the discharge flow

$$Q_f = A_f \sqrt{2g \left(h_{2i} - h_i\right),}$$
\[ Q_{sf} = C_q B \sqrt{2g \left( h_c - h_p \right)^{3/2}}, \]  

where \( C_q \) is the discharge coefficient, \( B \) the width of the weir and \( h_p \) the weir crest height.

Similarly to what has been done for the electro-mechanical sub-system, the hydraulic model has been implemented in the Matlab-based simulation environment by using Simulink/Simscape blocks.
3.3. Models calibration and validation

The aforementioned first-principle models include several parameters which can assume different values and so making the shape of the equations flexible while maintaining their structure. The nominal model parameters are provided from literature and technical data-sheet while others parameter values can be guessed by expert knowledge or can be estimated from real data. Anyway, in order to obtain a suitable representation of the processes of interest that satisfies pre-agreed criteria (e.g. goodness-of-fit or cost function), certain model parameters need to be adjusted around their nominal values. Here, the calibration procedure is carried out by comparing observed and simulated data. To this aim, an extensive experimental campaign has been carried out to obtain real data. In Fig. 9 an example of experimental test is shown: the considered input to the system is a triangular-wave reference signal to the driver while the considered output is the weir position. The data gained from the experimental tests have been split into a calibration dataset and a validation one. By exploiting the first dataset, we adjust the values of model parameters by solving offline an optimization problem that minimize the Root Mean Squared Error (RMSE) between the simulated output and the target one. Finally, the calibrated model is validated, i.e. it is tested to check its performances in the validation dataset. It is worth noticing that, validation is always appropriate, in view of the uncertainty affecting the models and for this reason it is appropriate to use different data for the calibration and validation steps. By way of an example, Fig. 8 shows the comparison between target and output data when the calibration of certain electro-mechanical parameters is carried out. Specifically, Fig. 8a refers to the calibration step: certain electro-mechanical sub-system parameters (e.g. the worm gear friction loss coefficient) have been adjusted by using an heuristic technique (Beghi, Cecchinato, & Rampazzo, 2011) that minimize the RMSE. Beside this, Fig. 8b is related to the validation step and we can see that the outputs and the targets are sufficiently close each other, indeed the RMSE equals 0.56 mm.

4. Simulation results

We consider here certain relevant simulations, the results of which are shown in Fig. 9. In particular, the wave height (blue line, Fig. 9a) presents a time delay and an amplitude reduction compared with the position of the sharp edge of the weir (orange line), due to the propagation processes of the wave. The model output predictions restate that is necessary to generate the desired wave directly in front of the lagoon in order to be sure of the wave characteristics at the lagoonal inlet. A comparison between the model output predictions with the measurements of the ultrasonic probe, for the tide (blue markers), and in the inlet. A comparison between the model output predictions with the measurements of the ultrasonic probe, for the tide (blue markers), and in the lagoon in order to be sure of the wave characteristics at the lagoonal inlet. A comparison between the model output predictions with the measurements of the ultrasonic probe, for the tide (blue markers), and in the lagoon in order to be sure of the wave characteristics at the lagoonal inlet.

5. Model-free control

The artificial tide generation system exhibits non-linear behaviours with both fast dynamics (e.g. the electro-mechanical sub-system) and slow dynamics (e.g. the hydraulic sub-system), plus dead time (due to the water mass transport). It is also expected that certain system configurations, boundary conditions, and some system parameters may change during campaigns of experiments. Moreover, the control algorithm for the artificial tide generation apparatus has to be designed under some technological constraints, given by the fact that it has to be implemented as an upgrade of a traditional control unit, with limited computational and memory resources. From a practical point of view, the use of a standard regulator sounds good. On the other hand, due to the difficulty in adopting a model-based control approach and/or in setting up trial-and-error experiments for tuning e.g. PID parameters by inspecting the dynamic behaviour of the process output, we here adopt a model-free control approach, that is the intelligent PID (Bara, Fliess, Join, Day, & Djouadi, 2018; Fliess & Join, 2009, 2013; Join, Robert, & Fliess, 2010; Lafont, Balmat, Pessel, & Fliss, 2015; Rampazzo, Cervato, & Beghi, 2017).

This type of control technique is based on an elementary continuously update local modelling via the unique knowledge of the system input–output behaviour. By way of example, we consider a SISO system approximately governed by an unknown finite-dimensional ordinary differential equation:

\[
E(t, y, \dot{y}, \ldots, y^{(n)}, u, \dot{u}, \ldots, u^{(m)}) = 0,
\]

where \(u\) and \(y\) are the input and output variables respectively, whereas \(E : \mathbb{R}^{m+1} \times \mathbb{R}^{n+1} \rightarrow \mathbb{R}\) is assumed to be a sufficiently smooth function of its arguments. Let us assume that, for integer \(v, 0 < v \leq l\):

\[
\frac{\partial E}{\partial y^{(v)}} \neq 0. \tag{7}
\]

According to the Dini’s implicit function theorem, \(y^{(v)}\) can locally be expressed as follows:

\[
y^{(v)} = \mathcal{E}(t, y, \dot{y}, \ldots, y^{(v-1)}, y^{(v+1)}, \ldots, y^{(l)}, u, \dot{u}, \ldots, u^{(k)}), \tag{8}
\]

\[
\mathcal{E} \subseteq \mathbb{R}^{l+1} \times \mathbb{R}^{n+1} \times \mathbb{R}^{m+1}.
\]
with, the function $\xi : \mathbb{R} \times \mathbb{R}^l \times \mathbb{R}^{l+1} \to \mathbb{R}$. From (8), one can replace (6) by the following phenomenological ultra-local model which is only valid in a very short time interval:

$$y^{(\nu)} = F + au.$$  (9)

In (9), $F$ contains all structural information of the process while $a \in \mathbb{R}$ is a non-physical parameter, which is typically chosen iteratively, such that $F$ and $au$ are of the same magnitude. The derivation order $\nu$ is also chosen by experience (typically, $\nu$ is taken equals 1 or 2). If we assume that the measure of the output $y$ is available, then $F$ could be computed from (9) by means of $u, a,$ and of estimate of $y^{(\nu)}$, i.e. $\hat{y}^{(\nu)}$, as follows:

$$\hat{F} = \hat{y}^{(\nu)} - au,$$  (10)

where $\hat{u}$ is an approximate value of $u$ in order to avoid algebraic loops in the controller (e.g. $\hat{u}$ can be chosen as a past value of the control variable $u$).

Furthermore, we choose the closed-loop controller such as:

$$u = \frac{y^{(\nu)} - \hat{F} - \hat{E}(e)}{a},$$  (11)

where $y_0$ is the output reference trajectory and $e = y_0 - y$ is the tracking error. The controller $\hat{E}$ should be selected such that a perfect tracking is asymptotically ensured, i.e.:

$$\lim_{t \to \infty} e(t) = 0.$$  (12)

By combining (9) and (11), we obtain:

$$e^{(\nu)} + \hat{E}(e) = 0.$$  (13)

It is worth pointing out that $F$ does not appear anymore in (13), i.e. the unknown parts and disturbances of the plant vanish. The tuning of the controller $\hat{E}$ becomes, therefore, straightforward for obtaining a good tracking of the reference. This is a major benefit when compared to the tuning of conventional standard regulator. Indeed, the intelligent controller can be regarded as a feed-forward control based on the local plant model in combination with a conventional controller (Fig. 10).

By setting $\nu$ value and by choosing a standard regulator as $\hat{E}$, which ensures the desired behaviour, we could obtain different type of intelligent controllers as follows:

- $\nu = 1$, $\hat{E} = K_p e(t) \to$ i-P
- $\nu = 2$, $\hat{E} = K_p e(t) + K_d \dot{e}(t) \to$ i-PD
- $\nu = 1$, $\hat{E} = K_p e(t) + K_I \int e(t) \, dt \to$ i-PI
- $\nu = 2$, $\hat{E} = K_p e(t) + K_I \int e(t) \, dt + K_P \dot{e}(t) \to$ i-PID

The connection between the intelligent controllers and the conventional PDs was shown by D’Andréa-Novel, Fliess, Join, Mounier, and Steux (2010). In particular, the proof relies on a crude time-sampling of both types of regulators and it shows that the gains in a classic PI or PID take into account, if they are properly tuned, the estimated structural part of the intelligent controllers. Table 2 depicts the correspondence between the gains of sampled classic and intelligent controllers, where $k_p, k_i,$ and $k_d$ refer to standard regulators tuning gains, while $K_p, K_I,$ and $K_D$ correspond to intelligent controllers tuning parameters; $h$ is the sampling time interval. Moreover, the PI and PI-D result as follows:

$$\text{PI} \to k_p e(t) + k_i \int e(t) \, dt + k_d \dot{e}(t).$$  (14)

$$\text{PI-D} \to k_p e(t) + k_i \int e(t) \, dt + k_d \dot{e}(t) + k_d e(t).$$  (15)

The double integrals in (14) and (15) seem to be quite uncommon in control engineering, but may result useful in certain applications.

Last but not least, the intelligent controller may bring with it intrinsic advantages, such as those highlighted by Fliess and Join (2013):

- questions on the structure and on the parameter identification of systems might lose their importance if the need of a “good” mathematical modelling is diminishing;
- many effort on robustness issues with respect to a “poor” modelling and/or to disturbances may be viewed less important. As a matter of fact those issues disappear to a large extent thanks to the continuously updated numerical values of $F$ in (9).

5.1. Estimation of the process structural information

In order to estimate the structural information of the process $\hat{F}$ from (10), it is crucial to have available a good estimate of the differentiation of the output $y$ with respect to time. For example, if we consider the derivation order $\nu$ equal to 1, $\dot{y}$ can by inferred by using a peculiar feedback loop where the output of an integrator (i.e. the plant) has to track the reference $y$, Fig. 11. As a consequence, the integrator input can be regarded as an estimate for $\dot{y}$ (Horn & Reichhartinger, 2009). In particular, a robust exact differentiator scheme is used (Levant, 1998), where the controller $C$ implements the so-called super-twisting algorithm (Levant, 2007):

$$\dot{y} = z - \varphi \sqrt{|z|} \, \text{sign}(\xi).$$  (16a)

$$\xi = -k \, \text{sign}(\xi).$$  (16b)

and where $z$ is an auxiliary variable, whereas $\varphi$ and $k$ are positive constants. It is worth highlighting that, thanks to this approach, the error $\xi$ as well as its first-time-derivative are forced to zero in finite time (Levant, 2003).

Remark on stability margins and model-free control: stability margins, e.g. gain and phase margins (Astrom & Murray, 2008), are quite often utilized in order to check the control design of plants or, more exactly, of their mathematical models. Fliess and Join (2014) have extended calculations related to stability margins to the model-free techniques. In order to ensure satisfactory performances, it would

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Table 2

<table>
<thead>
<tr>
<th>Regulator</th>
<th>PI</th>
<th>i-P</th>
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<td>$-1/ah$</td>
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Fig. 10. Model-free control architecture: $r$ is the reference signal, $y$ is the process output, $\hat{F}$ is an estimation of the structural information of the process, and $u$ is the actuating signal generated by the controller.
6. Experimental results

Among the aforementioned intelligent controllers, we have chosen the i-PI configuration. This is based on the rationale that in the considered application the output reference trajectory usually increases/decreases its value over the time and, for example, it could be locally approximated by a ramp. Given a ramp reference trajectory, a controller with a double integrator is potentially able to avoid permanent tracking errors. Due to correspondence between the PI\(^2\) and the i-PI (Table 2), we have selected the intelligent-proportional–integral configuration. In particular, by exploiting the simulation environment, we have designed, tuned, and tested the i-PI. Along with the simulation experience, we have moved on to the control system real implementation.

6.1. Sinusoidal tide reference

By way of an example, we consider as tide reference a sinusoidal signal with amplitude equal to 0.75 [cm] and period equals 8 [min]. In particular, we compare the performance of a standard PI regulator (Aström & Hägglund, 2006; Visioli, 2006) with that of an intelligent-PI controller. The controllers gains have been initially set by using standard tuning rules (O’Dwyer, 2009; Skogestad, 2001; Ziegler & Nichols, 1942) and then they have been adjusted by means of trial-and-error procedures. The controllers parameters are shown in Table 3.

In Fig. 12a we can see the reference signal (the dashed black line), the output provided by the standard regulator (the blue line), and the output provided by the i-PI controller (the orange line). The intelligent PI is able to satisfactory tracks the reference, on the contrary by using the standard regulator the output is lagging behind the reference. The tracking error \(e\) and the controller output \(u\), for both controllers, are depicted in Figs. 12b and 12c, respectively. It is worth highlighting that, the PI controller exhibits an ITSE (Integral Time Squared Error) equal to 55060 [cm\(^2\) s] while the i-PI controller entails an ITSE equals 9980 [cm\(^2\) s], that is about 5 times smaller.

6.2. Ebb-dominated and flood-dominated tide references

In these experimental examples we consider more realistic references for the tide and the considered on-board controller is the i-PI one. Fig. 13 depicts some results concerning the ebb-dominated reference, while Fig. 14 refers to the flood-dominated case. In particular, Figs. 13a and 14a show the height of the tide provided by the ultrasonic probe (the blue line) and the sharp-edge weir vertical position provided by the potentiometer (the orange line). For the ebb-dominated tide, the output, which follows the reference with a small error (less or equal then about 0.1 [cm], Fig. 13b) and the ITSE, that is equal to 10 874 [cm\(^2\) s], confirm the satisfactory performance of the i-PI controller. The same can be said for the flood-dominated wave, which presents an ITSE equals 9980 [cm\(^2\) s], that is about 5 times smaller.

### Table 3

<table>
<thead>
<tr>
<th>Controllers parameters.</th>
<th>PI</th>
<th>i-PI</th>
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<tbody>
<tr>
<td>(k_p = 150 \cdot 10^3) [step cm(^{-1})]</td>
<td>(K_p = 175) [step cm(^{-1})]</td>
<td></td>
</tr>
<tr>
<td>(t_i = k_i/k_p = 7) [s]</td>
<td>(T_i = K_p/k_i = 1) [s]</td>
<td></td>
</tr>
<tr>
<td>(u = 5 \cdot 10^{-3}) [cm s(^{-1}) step(^{-1})]</td>
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It is worth highlighting that the sharp-edge weir vertical position signal (the orange line) presents an advance and an higher value of amplitude with respect to the tidal wave effectively generated.
(a) Comparison between the reference signal $r$, the water level measured by the ultrasonic probe $s$ and the weir position measured by the potentiometer $p$.

(b) The error between the reference and the output.

(c) Manipulated variable $u$, i.e. the input stepper-motor driver.

Fig. 13. Results obtained with the generation of an ebb-dominated tidal wave. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The blue line, due to the fact that the wave changes its form during the propagation from the weir to the lagoonal inlet. This observation restates the necessity of generate the desired wave directly in front of the lagoon in order to avoid unwanted transformation, that results in the impossibility of ensuring certain tidal forcing characteristics at the lagoonal inlet. Figs. 13c and 14c show the value of the manipulated variable $u$, calculated by the i-PI as input for the stepper-motor driver, for the ebb-dominated and the flood-dominated tide, respectively. It is perhaps worth stressing that smooth profiles of $u$ avoid unwanted additional stresses on the stepper-motor and contribute to a longer life of
Fig. 15. Results obtained with the generation of an ebb-dominated tidal wave.

(a) Comparison between the reference signal $r$, the water level measured by the ultrasonic probe $s$ and the weir position measured by the potentiometer $p$.

(b) Comparison between the velocity calculated $r$ and from experimental data $s$.

(c) Velocity-stage plot: calculated $r$ and from experimental data $s$.

Fig. 16. Results obtained with the generation of a flood-dominated tidal wave.

(a) Comparison between the reference signal $r$, the water level measured by the ultrasonic probe $s$ and the weir position measured by the potentiometer $p$.

(b) Comparison between the velocity calculated $r$ and from experimental data $s$.

(c) Velocity-stage plot: calculated $r$ and from experimental data $s$.

7. Conclusion

CACSD software tools are very useful to simulate relevant system dynamics for a first assessment of the different control strategies. We
have developed and tested a Matlab-based simulation environment for the multi-domain artificial tidal wave generation system. In particular, we have used Simulink traditional block diagrams and Simscape components to integrate different causal and acausal sub-models in order to make them transparent to the users, to preserve their testability, and to gain the necessary user confidence. A comparison between simulations and real experiments shows that the simulation tool is able to correctly reproduce the relevant system dynamics. Once tested different control strategies with the simulation tool, we have compared the performance of a standard regulator with those of an i-PI on the real experimental apparatus. It is worth noticing that, the intelligent PI can be regarded as a feed-forward control based on the local plant models in combination with a conventional PI algorithm. For these reasons the i-PI reaches a satisfactory balance between performance and architectural complexity. From a practical point of view, we have performed various tests on the experimental apparatus (e.g. by reproducing flood dominated and ebb dominated tidal flows). From the experimental tests, we can conclude that the performance of the i-PI model-free controller is ever better than that of the standard regulator. In particular, the use of this model-free approach allows to adequately control the system without resorting to tedious and time-consuming controller retuning when changes of the system operating conditions or time-varying parameters arise.

References


