A mathematical model to investigate the effects of intravenous fluid administration and fluid loss

Citation for published version (APA):

Document license:
CC BY-NC-ND

DOI:
10.1016/j.jbiomech.2019.03.002

Document status and date:
Published: 01/05/2019

Document Version:
Publisher’s PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher’s website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the “Taverne” license above, please follow below link for the End User Agreement:
www.tue.nl/taverne

Take down policy
If you believe that this document breaches copyright please contact us at:
openaccess@tue.nl
providing details and we will investigate your claim.

Download date: 17. Aug. 2019
A mathematical model to investigate the effects of intravenous fluid administration and fluid loss

Tilaï T. Rosalina\textsuperscript{a,*}, R. Arthur Bouwman\textsuperscript{b,c,d}, Marc R.H.M. van Sambeek\textsuperscript{a,c}, Frans N. van de Vosse\textsuperscript{a}, Peter H.M. Bovendeerd\textsuperscript{a}

\textsuperscript{a}Department of Biomedical Engineering, Eindhoven University of Technology, P.O. Box 513, 5600 MB Eindhoven, the Netherlands
\textsuperscript{b}Department of Electrical Engineering, Eindhoven University of Technology, P.O. Box 513, 5600 MB Eindhoven, the Netherlands
\textsuperscript{c}Catharina Hospital Eindhoven, Michelangeloalaan 2, 5623 EJ Eindhoven, the Netherlands
\textsuperscript{d}Philips Research Eindhoven, High Tech Campus 34, Eindhoven, the Netherlands

\textbf{Article info}

\textbf{Article history:}
Accepted 1 March 2019

\textbf{Keywords:}
Fluid administration
Mathematical models
Transcapillary fluid exchange
Model assisted decision support

\textbf{Abstract}

The optimal fluid administration protocol for critically ill perioperative patients is hard to estimate due to the lack of tools to directly measure the patient fluid status. This results in the suboptimal clinical outcome of interventions. Previously developed predictive mathematical models focus on describing the fluid exchange over time but they lack clinical applicability, since they do not allow prediction of clinically measurable indices. The aim of this study is to make a first step towards a model predictive clinical decision support system for fluid administration, by extending the current fluid exchange models with a regulated cardiovascular circulation, to allow prediction of these indices. The parameters of the model were tuned to correctly reproduce experimentally measured changes in arterial pressure and heart rate, observed during infusion of normal saline in healthy volunteers. With the resulting tuned model, a different experiment including blood loss and infusion could be reproduced as well. These results show the potential of using this model as a basis for a decision support tool in a clinical setting.

© 2019 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

\textbf{1. Introduction}

Intravenous fluid infusion, to compensate for perioperative fluid loss due to bleeding, perspiration and evaporation, is a common procedure to maintain arterial blood pressure and thereby tissue perfusion. However, part of the administered fluid will shift to the interstitial space, causing edema buildup that may eventually compress tissue microvasculature, disturb tissue perfusion and could lead to organ failure. Especially in the critically ill, these 'fluid shifts' can be large and unpredictable, due to changes in endothelial permeability and hydrostatic and osmotic pressure (Holte et al., 2002; Brandstrup, 2006). The optimal protocol for fluid administration depends on the intra- and extravascular fluid status of the patient. This fluid status is not directly measurable, and it cannot be easily deduced from indirect measurements. Additionally there is a large inter-patient variability, which makes evidence-based predictions difficult. Hence, it remains difficult to estimate the amount of fluid needed to compensate perioperative fluid loss. A patient specific mathematical model might be used to assist in determining the optimal fluid protocol.

In literature various mathematical models have been presented that focus on fluid administration and (re-) distribution. Some models describe fluid exchange between intra- and extravascular spaces using Starling’s law, based on hydrostatic and osmotic pressures (Chapple et al., 1993; Xie et al., 1995; Gyenge et al., 1999, 2003; Mazzoni et al., 1988; Carlson et al., 1996; Wolf and Watson, 1989; Wolf and Deland, 2011; Wolf, 2013). Other models use a more phenomenological volume kinetics approach (Hahn and Svensén, 1997; Svensén et al., 1999; Hahn, 2010, 2017). Since the first type of models are based on laws of physics and physiology, they provide a stronger basis to predict the internal condition and the clinically observed information of a perioperative patient.

However, previously published models of this type have a limited representation of the cardiovascular circulation and lack information on arterial pressure and heart rate. Since arterial pressure is one of the important clinically available measurements used to guide fluid administration, it is hard to apply these models clinically.

We aim to develop a decision support model that can eventually assist in fluid administration to critically ill patients based
on clinically available information such as arterial pressure and heart rate. In this study we extend a fluid exchange model (Xie et al., 1995) with a model of cardiovascular function (Jongen et al., 2016). Model parameters are partly taken from literature (Gyenge et al., 1999, 2003; Jongen et al., 2016), and partly determined from a fit to an experimental dataset of saline infusion (Watenpaugh et al., 1992). We evaluate our model by simulating another volunteer dataset of fluid administration in hypo- and normovolemia. Finally, we compare our model, with a regulated cardiovascular system, to the original fluid exchange model.

2. Methods

The model (Fig. 1) combines submodels of cardiovascular hemodynamics, cardiovascular regulation, fluid exchange, and renal function.

2.1. Submodel: fluid exchange

The fluid exchange model is taken from Xie et al. (1995). It consists of a vascular and an interstitial compartment. The vascular compartment consists of plasma (with volume \( V_{PL} \) in ml), red blood cells (\( V_{RBC} \) in ml), and proteins (with mass \( M_{PR} \) in g), where the volume occupied by the proteins is neglected. The ratio of red blood cells to plasma is given by the hematocrit (\( H_r \)):

\[
H_r = \frac{V_{RBC}}{V_{PL}} \times 100\%.
\]

The concentration of proteins in the plasma (\( c_{PL} \) in \( \text{g} \)) is calculated as:

\[
c_{PL} = \frac{M_{PR}}{V_{PL}}.
\]

The interstitial compartment consists of fluid, with volume \( V_I \), and proteins, with mass \( M_I \). A part of this volume, the excluded volume \( V_{ex} \), is not available as a solvent for protein. This volume includes other macromolecules such as collagen and fibrin (Xie et al., 1995). Therefore we distinguish between interstitial protein concentration (\( c_{I} \)), and available interstitial protein concentration (\( c_{IA} \):

\[
c_I = \frac{M_I}{V_I}, \quad c_{IA} = \frac{M_I}{(V_I - V_{ex})}.
\]

The exchange of fluid between compartments satisfies the mass balance:

\[
\frac{dV_I}{dt} = J_{intake} + J_{inf} - J_{IV,TC} + J_{IV,L} - J_I - J_{V,bleed}.
\]

The transcapillary fluid exchange (\( J_{IV,TC} \)) is described by the Starling hypothesis:

\[
J_{IV,TC} = k_f \cdot (p_{cap} - p_I - \sigma (p_{cap} - p_I)) - \tau \cdot \frac{J_{IV,TC}}{J_{IV,TC}^{max}}.
\]

Here, \( J_{intake} \) is the basal intake in normovolemia in \( \frac{ml}{s} \), \( J_{inf} \) is the infused fluid flow in \( \frac{ml}{s} \), \( J_{IV,TC} \) is the transcapillary fluid flow in \( \frac{ml}{s} \), \( J_{IV,L} \) is the lymph flow in \( \frac{ml}{s} \), \( J_I \) is the urine flow in \( \frac{ml}{s} \), \( J_{V,bleed} \) is the plasma loss due to hemorrhage \( (J_{bleed}) \) in \( \frac{ml}{s} \) and \( J_{ins} \) is the insensible fluid loss in \( \frac{ml}{s} \). It holds that:

\[
J_{V,bleed} = J_{bleed} \cdot (1 - H_c).
\]

The transcapillary fluid exchange (\( J_{IV,TC} \)) is described by the Starling hypothesis:

\[
J_{IV,TC} = k_f \cdot \frac{p_{cap} - p_l - \sigma (p_{cap} - p_l)}{L}.
\]

Here, \( k_f \) is the membrane permeability constant in \( \frac{ml}{mmHg \cdot s} \), \( p \) in mmHg is the hydrostatic pressure, \( \sigma \) in mmHg is the protein osmotic pressure, with subscripts cap for the capillaries and I for the interstitium, and \( \sigma [-] \) is the reflection coefficient. The capillary pressure is computed from the cardiovascular model, which will be described in Section 2.2. The interstitial pressure is calculated by empirical equations taken from Chapple et al. (1993), depending on the state of hydration:

\[
p_I = \begin{cases} 
    p_{IN} + \frac{(V_I - V_{ex})}{C_{inter}} & V_I \leq V_{IN} \\
    p_{IN} + \frac{(V_I - V_{ex})}{C_{inter}} & V_{IN} < V_I < V_{Laster} \\
    p_{Laster} + \frac{(V_I - V_{ex})}{C_{inter}} & V_I \geq V_{Laster}
\end{cases}
\]

Here, \( p_{IN} \) is the interstitial pressure in normovolemia \( (V_{IN}) \) and \( p_{Laster} \) is the interstitial pressure at the threshold for hypervolemia \( (V_{Laster}) \). In the normovolic range \( (V_{IN} < V_I < V_{Laster}) \) \( p_I \) is determined by the normal interstitial compliance \( (C_{inter}) \). The compliances

---

**Fig. 1.** Schematic overview of the mathematical model: the left ventricle (LV) generates a blood flow \( (J_{inf}) \) that passes through the arteries (art), capillaries (cap) and veins (ven) facing a total resistance that is composed of an arterial and a venous part \( (R_{ven}, R_{cap}) \). The baroregulation responds to the deviation of the mean arterial pressure \( (p_{art}) \), heart contractility \( (E_{max}) \) and cycle time \( (T_{cycle}) \). The Bainbridge reflex responds to the deviation of the mean venous pressure \( (p_{ven}) \) from the venous reference pressure \( (p_{ven,ref}) \). The fluid exchange with the environment is determined by a basal fluid intake \( (J_{intake}) \), fluid infusion \( (J_{inf}) \), bleeding \( (J_{bleed}) \), urine production \( (J_U) \) and insensible losses \( (J_{ins}) \). The fluid exchange between the vascular compartment and the interstitium \( (int) \) consists of transcapillary fluid flow \( (J_{IV,TC}) \) and lymphatic fluid \( (J_{IV,L}) \). These fluid flows are related to corresponding protein flows, \( J_{IV,TC} \) and \( J_{IV,L} \), respectively.
\( C_{\text{ ALTER}} \) and \( C_{\text{ HENDER}} \) determine \( p_i \) in hyper- and hypovolemia, respectively.

Finally, the osmotic pressure is based on the protein concentrations as follows:

\[
\pi_{\text{CAP}} = k_{\text{Prot}} \cdot c_R, \quad \pi_i = k_{\text{Prot}} \cdot c_I, \tag{9}
\]

where \( k_{\text{Prot}} \) is an empirical proportionality coefficient.

The lymph flow \( J_{LY} \), which causes water to be constantly transported back into the intravascular space, depends on the interstitial pressure (Chapple et al., 1993):

\[
J_{LY} = \begin{cases} 
0 & p_i < p_{\text{EX}} \\
J_{\text{LN}} \cdot \frac{p_{\text{IN}} - p_{\text{EX}}}{\pi_{\text{LN}} - p_{\text{EX}}} & p_{\text{LS}} < p_i < p_{\text{LN}} \\
J_{\text{LN}} + L S \cdot (p_i - p_{\text{IN}}) & p_i > p_{\text{IN}} 
\end{cases} \tag{10}
\]

Here \( J_{\text{LN}} \) is the normal lymph flow, \( p_{\text{EX}} \) is the pressure corresponding to the volume \( V_{\text{EX}} \), and \( L S \) is the combination of a tissue permeability \( (L) \) and surface area \( (S) \) in \( \text{ml} \text{mgHg}^{-1} \).

The elimination of fluids in steady state occurs through insensible losses \( J_{\text{INS}} \), assumed to be constant, and urine production \( J_U \). \( J_U \) is assumed to be linearly related to plasma volume (Gjenge et al., 2003):

\[
J_U = \begin{cases} 
J_U^0 + k_{\text{ID}} \cdot \frac{V_{\text{PL}} - V_{\text{PLN}}}{\pi_{\text{PLN}}} & V_{\text{PL}} \leq V_{\text{PLN}} \\
J_U^0 + k_{\text{DE}} \cdot \frac{V_{\text{PL}} - V_{\text{PLN}}}{\pi_{\text{PLN}}} & V_{\text{PL}} > V_{\text{PLN}} 
\end{cases} \tag{11}
\]

Here \( J_{\text{IN}} \) is the normal urine production at normal plasma volume \( (V_{\text{PLN}}) \) and \( k_{\text{ID}} \) and \( k_{\text{DE}} \) govern the change in urine production at depleted and elevated plasma volumes, respectively.

We assume that protein flows (in \( \mu \)l) are only associated with the transcapillary protein flow \( J_{\text{MTC}} \), lymph protein flow \( J_{\text{ML}} \) and bleeding \( J_{\text{BLEED}} \). Thus the following mass balances hold:

\[
\frac{dM_R}{dt} = -J_{\text{MTC}} + J_{\text{ML}} - J_{\text{BLEED}} \cdot c_R \tag{12}
\]

\[
\frac{dM_I}{dt} = J_{\text{MTC}} - J_{\text{ML}}. \tag{13}
\]

The transcapillary protein flow \( J_{\text{MTC}} \) is based on Kedem and Katchalsky (1958):

\[
J_{\text{MTC}} = J_{\text{VTC}} \cdot (1 - \sigma) \cdot \left[ \frac{c_R - c_I \exp \left( \frac{-f_{\text{PL}} (1 - \sigma)}{p} \right)}{1 - \exp \left( \frac{-f_{\text{PL}} (1 - \sigma)}{p} \right)} \right], \tag{14}
\]

with \( p = \frac{h}{h} \) the protein permeability \( (D) \) is the protein diffusion constant, and \( h \) is the membrane thickness and the surface area \( S \), commonly treated as one parameter \( P_S \), (protein permeability-surface area product of the capillary).

The lymphatic flow of protein \( J_{\text{ML}} \) is considered to occur through convection only:

\[
J_{\text{ML}} = J_L \cdot c_l \tag{15}
\]

Finally, to account for bleeding, the following mass balance for red blood cells holds:

\[
\frac{dV_{\text{RBC}}}{dt} = J_{\text{BLEED}} \cdot H_C. \tag{16}
\]

2.2. Submodel: cardiovascular circulation

To determine the capillary pressure \( (p_{\text{CAP}}) \) used in (7), we implemented a cardiovascular model of the cycle-averaged systemic circulation (Jongen et al., 2016).

The model for the left ventricle is based on Hoppensteadt and Peskin (2002). Cardiac output \( J_{CO} \) is defined as:

\[
J_{CO} = \frac{V_{\text{STROKE}}}{T_{\text{CYCLE}}}. \tag{17}
\]

Here the stroke volume \( (V_{\text{STROKE}}) \) is determined by end diastolic volume \( (V_{\text{ED}}) \) and end ejection volume \( (V_{\text{EE}}) \), which in turn depends on the filling \( (p_{\text{FILL}}) \) and ejection pressure \( (p_{\text{EE}}) \) of the heart. \( T_{\text{CYCLE}} \) is cardiac cycle time. We consider a linear pressure-volume relation for diastole and end ejection (Suga et al., 1973):

\[
p_{\text{FILL}} = E_{\text{FILL}} (V_{\text{ED}} - V_{\text{EE}}); \quad p_{\text{EE}} = E_{\text{MAX}} (V_{\text{EE}} - V_{\text{ED}}) \tag{18}
\]

with \( E_{\text{MAX}} \) the maximal elastance and \( E_{\text{FILL}} \) the passive elastance of the left ventricle and \( V_{\text{ED}} \) in the left ventricle volume intercept.

For the systemic nodes, the following constitutive equations hold for the mean arterial pressure \( (p_{\text{ART}}) \) and venous pressure \( (p_{\text{VEN}}) \):

\[
p_{\text{ART}} = \frac{V_{\text{ART}} - V_{\text{ART,0}}}{C_{\text{ART}}}; \quad p_{\text{VEN}} = \frac{V_{\text{VEN}} - V_{\text{VEN,0}}}{C_{\text{VEN}}}. \tag{19}
\]

Here \( V_{\text{ART}} \) is the arterial blood volume, \( V_{\text{ART,0}} \) is the arterial unstressed volume, \( C_{\text{ART}} \) is the arterial compliance, \( V_{\text{VEN}} \) is the venous volume, \( V_{\text{VEN,0}} \) is the unstressed venous volume and \( C_{\text{VEN}} \) is the venous compliance. Since we assume a cycle-averaged system, without pulsatility and valves, we can assume \( p_{\text{ART}} = p_{\text{ART}} \) and \( p_{\text{VEN}} = p_{\text{VEN}} \). Therefore the cardiac output can be calculated as follows:

\[
J_{CO} = \frac{1}{T_{\text{CYCLE}}} \left( \frac{p_{\text{VEN}} - p_{\text{ART}}}{E_{\text{MIN}} - E_{\text{MAX}}} \right). \tag{20}
\]

At the same time it holds that:

\[
J_{CO} = \frac{p_{\text{ART}} - p_{\text{VEN}}}{R_{\text{ART}} + R_{\text{VEN}}}, \tag{21}
\]

with \( R_{\text{ART}} \) and \( R_{\text{VEN}} \) the arterial and venous capillary resistances in \( \text{mmHg} \text{ml}^{-1} \) respectively.

Combining (19)–(21) we can determine the arterial and venous pressures analytically:

\[
p_{\text{ART}} = \frac{k_2}{k_0 C_e + k_1 C_o} (V_{\text{ART}} - V_{\text{ART,0}} - V_{\text{VEN}}), \quad p_{\text{VEN}} = \frac{k_2}{k_0 C_e} \tag{22}
\]

with:

\[
C_o = C_{\text{ART}} + \frac{1}{2 k_2}; \quad C_e = C_{\text{VEN}} + \frac{1}{2 k_2}; \quad k_0 = \frac{1}{k_{\text{ART}}}, \quad k_2 = \frac{1}{k_{\text{VEN}}}, \tag{23}
\]

and

\[
f_H = \frac{1}{T_{\text{CYCLE}}}. \tag{24}
\]

Finally, the capillary pressure that is used in (7) is calculated by:

\[
p_{\text{CAP}} = p_{\text{VEN}} + J_{CO} \cdot R_{\text{CAP}}. \tag{25}
\]

2.3. Submodel: cardiovascular regulation

Cardiovascular regulation is modelled by two pathways: baroregulation and the Bainbridge reflex. We model the baroregulation based on Wesseling and Settels (1985) and Jongen et al. (2016). A change in arterial pressure leads to a response of four cardiovascular effectors; the cardiac contractility \( (E_{\text{MAX}}) \), cycle time \( (T_{\text{CYCLE}}) \), precapillary peripheral resistance \( (R_{\text{CAP}}) \) and venous unstressed volume \( (V_{\text{VEN,0}}) \). Due to our large timescale, the model has been simplified by neglecting the effector time delays.
and low pass filters in the original model. The change in arterial pressure is transformed into a normalised receptor signal $-1 \leq b(t) \leq 1$, through a sigmoidal receptor function:

$$b(t) = \frac{2}{1 + \exp(-k \cdot (p_{art}(t) - p_{ref}))} - 1,$$  

(26)

where $k$ controls the sensitivity of the receptor and $p_{ref}$ is the reference mean arterial pressure.

This is translated into the receptor signal $(r(t))$ after passing through a low pass filter:

$$\frac{dr(t)}{dt} = \frac{1}{\tau_r}(b(t) - r(t)),$$  

(27)

where $\tau_r$ is the low pass filter receptor time constant. The change in $E_{max}$, $R_{art}$, and $V_{ven.0}$ is calculated by effector specific gains $k_r$, $k_g$ and $k_v$:

$$E_{max}(t) = E_{max.0} \cdot (1 + k_r \cdot r(t));$$

$$R_{art}(t) = R_{art.0} \cdot (1 + k_g \cdot r(t));$$

$$V_{ven.0}(t) = V_{ven.0.0} \cdot (1 + k_v \cdot r(t));$$  

(28)

where $E_{max.0}, R_{art.0}$ and $V_{ven.0.0}$ represent the steady state values for the effectors.

The change in $T_{cycle}$ is also affected by the Bainbridge reflex, i.e., the positive chronotropic response of the heart to stretch-activated channels in the atria. In hyperkalemia the atria are stretched and this results in extra stimulation of the sino-atrial node, thereby increasing the heart rate. To account for this increase in heart rate we have added a receptor signal $(r_0)$, calculated by a normalised change in venous pressure $p_{ven}$ with respect to a reference value $(p_{ven.ref})$ taken as a substitute for right atrium pressure:

$$r_0(t) = \frac{p_{ven}(t) - p_{ven.ref}}{p_{ven.ref}}.$$  

(29)

The cycle time is finally calculated by:

$$T_{cycle}(t) = T_{cycle.0} \cdot (1 + k_f \cdot r(t) + k_{en} \cdot r_0(t)).$$  

(30)

where $k_f$ is the baroregulation effector gain and $k_{en}$ is the Bainbridge effector gain.

### 2.4. Parameter estimation

The cardiovascular system was tuned to yield normal steady state hemodynamics for a 70 kg subject, characterised by $p_{art} = 93$ mmHg, $p_{cap} = 11$ mmHg, $p_{ven} = 5$ mmHg, CO = 5000 ml/min and EF = 67%.

Most regulation parameters are based on estimations of Wesseling and Settels (1985). For the regulation, $p_{ref}$ is set to normal arterial pressure (93 mmHg) and $p_{ven.ref}$ is set to normal venous pressure (5 mmHg). To simulate the response of the model to perturbations we fitted the cardiovascular model output ($\Delta p_{art}, \Delta HR$ and $\Delta En$) to a dataset from literature (Watenpaugh et al., 1992). In this experimental study the effect of infusion of 30 ml/kg of normal saline, with an infusion rate of 100 ml/min was analysed in seven male volunteers of 78 kg. By manual fitting of $k_g$ and $k_{en}$, the responses of the change in resistance and change in heart rate were tuned to available experimental data. To obtain correct changes in total arterial pressure, the rest of the effect was tuned by fitting $k_r$.

Settings for many parameters in the fluid exchange model are taken from Xie et al. (1995). Settings for parameters $J_{INS}, PS$ and $J_{bleed}$ were computed to satisfy steady state conditions. Hence, (4), (5), (12) and (14), are assumed to be equal to zero. In normal conditions we assume no intravenous infusion ($J_{inf} = 0$) or bleeding ($J_{bleed} = 0$). Hence, for the sum of the plasma and the interstitial volume it holds that:

$$J_{inake} = J_{ins} + J_{UN}$$  

(31)

After setting protein concentrations to values taken from Gyenge et al. (1999), we can determine $J_{IN}$ and $PS$ analytically, by combining (10) and (14) with:

$$J_{inake} - J_{VTC} + J_{VLC} - J_{U} = 0,$$  

(32)

and:

$$J_{MTC} - J_{ML} = 0.$$  

(33)

The fluid distribution results during infusion ($\Delta V_{TC}, \Delta V_{L}$ and $\Delta V_{U}$), were fitted to the experimental results by changing $k_f$ and $k_{en}$. All model parameter values are listed in Table 1.

### 2.5. Simulations

The model was implemented in MATLAB R2014b. Differential equations are solved by an Euler forward integration scheme with a time step of 0.1 s. First, the simulations for parameter estimations as described in Section 2.4 were performed. Secondly, to demonstrate the predictive value of the model on an independent dataset, we simulated an experiment presented by Drobin and Hahn (1999) without additional fitting. There, the authors infused 25 ml/kg in 10 healthy volunteers (with mean bodyweight of 76 kg), being normovolemic or hypovolemic (after induced haemorrhage of 900 ml in 15 min). Experimental and model computed changes of the plasma volume and total urine production at the end of the experiment could be directly compared.

Lastly, we compared our fluid exchange model, with the more complex regulated cardiovascular system, to the fluid exchange model as described in Xie et al. (1995). To this end, we simplified our cardiovascular circulation model to a ‘Xie-like’ model by replacing $E_{max}$ and $E_{art}$ by a single elastance value $E_{IV}$, such that the total compliance of the circulation model was identical to the one used by Xie et al. Due to this simplification we also had to exclude the baroregulation. To solely evaluate the role of the baroreflex, we performed additional simulations with our extended model without baroregulation.

### 3. Results

#### 3.1. Simulation of the experiment by Watenpaugh et al. (1992)

To reproduce the experimental data, obtained by Watenpaugh et al. (1992), we manually fitted $k_f, k_{en}, k_g$ and $k_{nr}$, presented in Table 1. Computed results match the experimental results, demonstrating that the model was fitted to the experiment successfully. The changes in volume (per kg body mass), heart rate and arterial pressure in the model and experiment are shown in Fig. 2. During infusion, $p_{art}$ and $HR$ increase with a maximal value of 9 mmHg and 15 bpm, respectively. Maximal $p_{ven}$ is 5.8 mmHg post-infusion. The simulated change in HR can be attributed to a decrease of 10 bpm and increase of 25 bpm, as a result of the baroregulation and Bainbridge reflex. At the end of infusion, the change in plasma and interstitial volume is 11.4 ml/kg and 21.5 ml/kg, respectively. After infusion $p_{cap}$ and $p_{art}$ return towards normal values. However, at 180 min post infusion $HR$ (+3 bpm), and plasma volume (+2.4 ml/kg) are still elevated. Eventually, 14.3 ml/kg urine is produced at the end of the experiment. Interstitial volume decreases more gradually than plasma volume and is still elevated by 11 ml/kg at the end of simulation, which is reflected in an elevated urine production of 11.8 ml/kg compared to a normal production of 2.6 ml/kg.
3.2. Simulation of the experiment by Drobin et al. (1999)

In Fig. 3, the simulated and experimental (Drobin and Hahn, 1999) changes in volume distribution in hypo- and normovolemia are shown. As in the experiment, changes are reported with respect to the start of infusion, set at \( t = 0 \) for both scenarios. In the normovolemic simulation, infusion causes a maximal change in plasma volume \( 10.3 \text{ ml/kg} \) also corresponds to the experimental results. The difference between hypo- and normovolemia results is most pronounced in the simulated urine production. Cumulative urine production at 180 min post infusion is reported to be \( 12.3 \pm 1 \text{ ml/kg} \) and \( 9.7 \pm 2 \text{ ml} \) in normo-, and hypovolemia, respectively. The model captures this in the normovolemic case \( (11.4 \text{ ml/kg}) \), but not in the hypovolemic case \( (3.6 \text{ ml/kg}) \). This results in an elevated interstitial volume in the latter case.

3.3. Comparison to the ‘Xie-like’ model

To further evaluate our extended model, we also simulated the Watenpaugh experiment with our reduced ‘Xie-like’ model, that resembles the model by Xie et al. (1995), as shown in Fig. 2. The ‘Xie-like’ model does not include \( P_{\text{ret}} \) and \( HR \). As compared to our extended model, it does predict an increased maximum rise in \( P_{\text{cap}} \) \( (15.1 \text{ vs. } 13.1 \text{ mmHg}) \). Consequently, more fluid is transported from the plasma into the interstitium and urine production is reduced at the end of the experiment by \( 2 \text{ ml/kg} \).

Finally, the effect of regulation was evaluated by simulating the Watenpaugh experiment without baroregulation (Fig. 2). This results in an increased \( P_{\text{ret}} \) \( (38 \text{ mmHg vs. } 9 \text{ mmHg post infusion}) \) and no changes in \( HR \). Results for changes in capillary pressure, plasma and interstitial volume, and urine production are similar to those of the ‘Xie-like’ model.

4. Discussion

Optimisation of perioperative fluid administration remains difficult due to high patient variability and the lack of tools to directly measure patient fluid status. Mathematical models have the potential of improving fluid administration protocols. Previously developed mathematical models focussed on describing the fluid exchange over time but they lacked clinically measurable indices such as heart rate and arterial blood pressure. The aim of our study was to make a first step towards a clinically applicable fluid
Fig. 2. Simulation of the experiment of Waterpaugh et al. (1992), with 30 ml/kg saline infusion from t = 0 to t = 23 min; experimental results are shown in symbols; simulation results are shown in solid lines, for the model with regulation, without regulation and the 'Xie-like' model. Left: change in mean arterial pressure (ΔP_{part} in mmHg), absolute capillary pressure (P_{cap} in mmHg) and change in heart rate (ΔHR in bpm). Right: scaled changes in plasma (ΔV_{pl} in ml/kg), interstitial (ΔV_{i} in ml/kg) and urine volume (ΔV_{u} in ml/kg).

Fig. 3. Simulation of the experiment by Drobin et al. (1999); results of 25 ml/kg saline infusion in a normovolemic and hypovolemic state. Left: the change in mean arterial pressure (ΔP_{part} in mmHg), absolute capillary pressure (P_{cap} in mmHg), change in heart rate (ΔHR in bpm). Right: scaled changes in plasma (ΔV_{pl} in ml/kg), interstitial (ΔV_{i} in ml/kg) and urine volume (ΔV_{u} in ml/kg). Experimental data (from Drobin et al. (1999)) are shown with symbols.
administration support model, by combining existing fluid exchange models (Xie et al., 1995; Gyenge et al., 2003) with a cardiovascular circulation model that includes baroregulation (Jongen et al., 2016) and the Bainbridge reflex. To the best of our knowledge this is the first time that such a coupling of short- and long term effects (cardiovascular regulation and fluid exchange, respectively) has been made.

Our model was used to study the effects of fluid infusion and blood loss in healthy volunteers. We could fit the model to predict the fluid exchange in one experiment (Watenpaugh et al., 1992) and subsequently reproduce results from another experiment (Drobin and Hahn, 1999) without further tuning. The Watenpaugh experiment was also simulated in our model without regulation, and in a ‘Xie-like’ model. Here, the increase in interstitial volume is approximately 10% lower in the extended model. We conclude that differences between our extended model and the ‘Xie-like’ model are mainly due to the addition of the (short term) regulation.

To achieve our goal of clinical decision support, the right balance between model complexity and accuracy must be made. The current goal was to study long term effects of fluid infusion on volume distribution in volunteers and their hemodynamic response in terms of mean arterial pressure and heart rate. Therefore, we chose to use a model for cycle-averaged hemodynamics without beat-to-beat information, which reduces the amount of parameters that needs to be estimated. We implemented the traditional Starling Eq. (7) to model whole-body transcapillary transport. Experiments (Michel and Philips, 1987) have shown that there is a distinction between transport in normal capillaries, where reabsorption of fluid seems absent, and fenestrated capillaries, where reabsorption is present. In recent years there has been an adaptation of the Starling equation, to better capture fluid exchange in capillaries (Adamson et al., 2004). However, we adopted the traditional Starling approach, since in our lumped parameter approach spatial variations, and hence variations in capillary type, are not taken into account. Lastly, we assumed urine production solely based on plasma volume, thereby omitting the effects of hormone regulation pathways such as the RAAS mechanism.

The three fitted parameters in the fluid exchange model (\(k_f, J_{UN}\) and \(PS\)) can be compared to previously presented values (Gyenge et al., 1999; Tatara et al., 2007). \(k_f\) is the determining factor for the maximum plasma expansion during infusion, and determines the persisting level after infusion. Our fitted value is 0.15 \(\text{ml/mmHg}\), which is high compared to 0.03 \(\text{ml/mmHg}\), reported in Gyenge et al., and 0.08 \(\text{ml/mmHg}\) in Tatara et al. (2007). But it is still within the range reported in literature (0.008–0.034 \(\text{ml/mmHg}\), Chapple et al. (1993)). \(PS\) and \(J_{UN}\) were derived from the condition of homeostatic equilibrium, i.e. from the condition of equal fluid intake and loss over time. Our calculated value for \(J_{UN}\) (0.009 \(\text{ml/min}\)) is low compared to literature values (0.02–0.04 \(\text{ml/min}\), Reddy, 1986). \(PS\) is hard to estimate from literature, however this parameter is closely correlated to the estimation of \(\sigma\) (0.8 – 0.99 –[7], Chapple et al., 1993). Ultimately, the transcapillary transport is not characterised by the individual values of these parameters, but by their combination (14), as expressed by the Péclet number: \(Pe = (1 - \sigma) J_{UN}/PS\). Comparing our results \((\sigma = 0.99, Pe = 0.0106)\) to Gyenge \((\sigma = 0.99, Pe = 0.0103)\) and Tatara et al. (2007) \((\sigma = 0.875, Pe = 0.046)\), shows the same order of magnitude. Thus, the Péclet number and therefore the combination of \(\sigma\) and \(PS\) is supported by literature.

Cardiovascular regulation is described by baroregulation and the Bainbridge reflex. In this study the venous pressure \((P_{c,av})\) is taken as a substitute for atrial pressure. This simplification is inherent to our choice of a simplified heart model. The change in HR by +15 bpm due to an increase of \(P_{c,av}\) by 1 mmHg, predicted by the model is supported by literature. Experimental data reported in Kohl et al. (1999) show an increase in the same order of magnitude (+8 bpm).

The predictive value of the model is demonstrated, since results of Drobin and Hahn (1999) are captured quite well with the same fitted parameters. Notably, there is an underestimation of urine production in the hypovolemic simulation (3.6 ml/kg vs 9.7 ml/kg). The urine production during hypovolemia is governed by parameter \(k_{UD}\) in (11), adopted from Gyenge et al. (2003), since this could not be fitted from the Watenpaugh dataset. Fitting of \(k_{UD}\) to the Drobin dataset proved to be impossible due to the fact that \(J_{UN}\) is four times smaller than the experimental \(J_{UN}\). However, in other studies (Gupta and Gan, 2016) a hypovolemic urine production of 1.5 ml/kg was reported, demonstrating considerable variation in between experimental data.

Our final goal is to develop a decision support model that can eventually assist in fluid administration to critically ill patients. It is known that fluid exchange in the perioperative period is altered. Perioperative medication for anaesthesia, analgesia and hemodynamic support affect (baro) regulation and renal function, which influences capillary fluid exchange. Additionally there can be effects of surgical inflammation causing capillary leakage (Brandstrup, 2006). In our model this can be accounted for in parameters related to membrane permeability (e.g. \(\sigma\) and \(k_f\) in 7).

Moreover, patients may suffer from comorbidities such as cardiovascular dysfunction, renal insufficiency and chronic hypertension. Therefore, in future work we need to extend the cardiac and renal model, to allow for realistic simulation of these pathologies.

For eventual use in a specific patient, suitable parameter values have to be found using data assimilation techniques. To gain more insight into the possibilities for parameter fixing and prioritisation, a structured sensitivity analysis (Eck et al., 2016) should also be performed. Additionally this could indicate which submodels should be explored further.

To conclude, we combined a simple model for cardiovascular hemodynamics with an existing model for fluid exchange for healthy volunteers enabling coupling of readily available clinical measurements to a fluid exchange model. This is the first step towards our general aim to develop a patient-specific decision support model to guide fluid administration.

Conflict of interest

Dr. R. Arthur Bouwman declares to be part-time employed at Philips Research Eindhoven. No further conflicts of interest are declared by the authors.

Acknowledgement

This work was performed within the IMPULS II perioperative monitoring framework in collaboration with Philips Eindhoven.

References


