Real-Time Expert-System Identification of Blood Pressure Measurement Accuracy During Renal Dialysis Treatment

Jill Stewart, Paul G. Stewart, *Senior Member, IEEE*, Rebecca Noble, Daniela Viramontes-Hörner, Maarten W. Taal, Nicholas M. Selby

***Abstract*— Objective: Current practice relies on intermittent occluding arm cuff measurements to monitor blood pressure during hemodialysis and to detect hypotension. However, systematic reviews report measurement accuracy challenges associated with brachial cuff measurements observed in the general population, and the factors contributing to inaccuracy are likely to be accentuated during dialysis treatment. There is currently no formal process to identify unreliable cuff BP measurements, and staff generally rely on *ad hoc* extra measurements and averaging readings. The objective of the activity described in this paper was to design a computational method to identify unreliable cuff measurements as they are taken and thus provide decision support to practitioners on dialysis units. Reliable intermittent systolic measurements are fundamentally important to both the calibration of continuous blood pressure measurements, and methodologies to predict the onset of hypotension.**

Methods: Patient studies with concurrent measurements of real-time continuous dialysis line pressure and intermittent systolic brachial cuff pressure during typically 4-hour, dialysis treatment sessions, revealed that some cuff measurements lay outside the prediction bounds associated with the expected quasi-linear (time-varying) relationship between arterial line and brachial pressure measurements. An AI expert system was designed, which embodies the mathematical relationships predicted by a system model, and a further complex rule-set which is able to discriminate between reliable and unreliable cuff measurements in real time based on sparse intermittent incoming data. The developed system was deployed on an observational patient study during hemodialysis treatments, outputting recommendations and justifications for accepting/rejecting cuff measurements. The accepted measurements were fed into a continuous, non-invasive systolic pressure estimator as calibration, enabling the reliability of the decisions made in the arterial line / systolic pressure domain to be verified in the systolic pressure / time domain. Results: Data collected from a prospective, observational patient study exhibited robust identification of unreliable arm cuff measurements, with the system operating as decision support. Continuous, non invasive, SBP predictions exhibited enhanced accuracy, in a typical example case, reducing mean error from 16.7mmHg **to** 6.8mmHg

Conclusion: A hybrid hardware/software system has been designed which utilises non-invasive continuous measurement of arterial dialysis line pressure to improve intermittent arm cuff measurements in order by identifying unreliable arm cuff measurements. The expert system computational core showed robust operation in accepting or excluding incoming arm cuff measurements. The devised system can support two requirements in future applications. Firstly, offering a repeatable and robust methodology to identify unreliable arm cuff measurements. Secondly to support the development of reliable SBP prediction algorithms to enable early intervention to predict hypotensive episodes and enable early intervention to prevent intradialytic hypotension.

Abbreviations: cardiovascular disease (CVD); end-stage kidney disease (EKD); intradialytic hypotension (IDH); blood pressure (BP), systolic blood pressure (SBP), diastolic blood pressure (DBP), Hemodialysis (HD), expert system (ES)

***Index Terms*— blood pressure measurement, dialysis, expert system, hypotension, measurement accuracy, real-time**

I. Introduction

INTRADIALYTIC hypotension is a factor leading to the development of cardiovascular disease (CVD) in patients receiving regular hemodialysis sessions [1], [2], commonly affecting between 15% to 50% of treatment sessions [3] and can lead to vascular access thrombosis, inadequate dialysis clearance, cardiac dysfunction and ultimately, mortality [5]. Prediction of blood pressure during treatment, and hence hypotension/hypertension, could significantly improve patient outcomes [4], [5] providing decision support to inform the choice of intervention including modulation of dialysis rate and/or duration, dialysate concentration and/or temperature on a per patient basis. IDH is generally a relatively sudden event, and can be defined as a decrease in systolic blood pressure greater than 20 mmHg or a decrease in mean arterial pressure by 10 mmHg, with an associated negative impact on patient well-being. Consequently, IDH can result in truncated dialysis treatments and increase the risk of coronary and cerebral

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Jill Stewart and Paul Stewart* are with the Institute of Engineering, Computing and Advanced Manufacturing, University of Cumbria, Lancaster, LA1 3JD U.K.

*corresponding author: paul.stewart@cumbria.ac.uk

Rebecca Noble, Daniela Viramontes-Hörner, Maarten W. Taal and Nicholas M. Selby are with the Centre for Kidney Research and Innovation, University of Nottingham, Nottingham NG7 2RD, U.K. and the Department of Renal Medicine, Royal Derby Hospital, Derby DE22 3NE, U.K.

ischemic incidents. Prediction of these events fundamentally relies on the accuracy of BP monitoring.

The regular measurement of brachial blood pressure by means of an upper arm occluding cuff has been highlighted as a key outcome mediator amongst patients receiving renal dialysis [6]–[8], and there is clear evidence that suboptimal BP and volume control result in negative patient outcomes [9]. Patient blood pressure (BP) is typically taken every thirty minutes during dialysis treatment on renal wards, generally by oscillometric BP monitors integrated with the dialysis machine, to inform the treatment management regime. Consequently inaccurate or misleading BP measurements [10] can devalue the quality of treatment outcomes. Studies of BP measurements taken under strict adherence to common guidelines compared to 'usual technique' show resultant variations in measurements and consequent treatment decisions based upon the two main measurement (oscillometric or auscultatory) methods [11], [12]. Furthermore, even subsequent to standardised training procedures, there are significant limits to the accuracy of BP measurements [13].

A. Sources of Innacuracy in BP measurements

A systematic review [10] of 328 studies quantifying BP measurement inaccuracy identified 29 potential sources of BP measurement inaccuracy which were related to the patient, device, procedure or observer. In the systematic review, effects of individual sources ranged from -23.6 to $+33mmHg$ SBP and -14 to $+23mmHg$ DBP. Regular BP measurement is included in standard patient monitoring protocols across dialysis units, and incorporate metrics which trigger appropriate interventions to the treatment. The review identifies factors which range from small to large in both $+ve$ and $-ve$ directions, with certain sources having bidirectional effects. Hence, it is impossible to identify how many sources of inaccuracy influence an individual reading, and calls into question monitoring protocols with single assessments of SBP taken outside of ideal conditions which are vulnerable to over- or under- estimation of SBP. Some representative sources of inaccuracy are presented here ($mmHg$):

- White-coat effect -12.7 to +26.7
- Talking during measurement +4 to +19
- Incorrect cuff size:
- Smaller Cuff +2.08 to +11.2
- Larger Cuff -3.7 to -1.45
- Arm lower than heart level +3.7 to +23
- Supine body position -10.7 to +9.5

In [21], further to BP measurement accuracy challenges observed in the general population [22], the authors observe that further complicating factors are encountered during dialysis treatment [23], [24]. There are elements directly linked to HD, for example;

- large BP variations caused by ultrafiltration and changes in blood volume
- inaccuracy in the oscillometric measurement method are exacerbated due to increased arterial wall rigidity associated with aging and diabetes, [25], [26]
- obesity causes oscillometric pulses to become increasingly weak
- cardiac arrhythmias, in particular atrial fibrillation, which are not uncommon during dialysis, affect both auscultatory and oscillometric device accuracy [27].

It has been also been observed that there are problems linked to procedural variations, especially as the generally accepted guidelines on the correct methodology of BP measurement [28] become difficult to follow in a busy dialysis unit. Occasionally incorrect cuff size are used [29]; cuffs can be sited on a wrong position on the patient's limb or fitted over thick clothing. Typically, single and not averaged BP measures are usually taken.

Currently, healthcare staff make judgments based on experience as to which BP measurements to accept and which to discount. A formal methodology to apply a more systematic approach would have clear advantages and reduce a potential source of variation in practice.

B. Relationship between measured SBP and arterial line pressure during dialysis treatment

We have previously described a mathematical model that approximates the relationship between arterial dialysis line pressure and brachial artery SBP measurements taken during dialysis treatment, by patient study [14]. The results from this observational study suggested that it is feasible to derive a continuous estimate of brachial pressure from continuous measurements of arterial line pressures via an empirically based (derived from measured data sets) mathematical model calculated in real time while noting that further work would be required to incorporate the effects of physiological changes during treatment, and importantly, external uncertainties and disturbances.

The challenges of unmodelled non-linearities, dynamics time-varying parameters in the development of an accurate BP estimation system have been addressed [15]. In particular, the problem of negating the effects of physiological parameter time variance by novel application of an iterative learning run-to-run modelling methodology to a parameterised BP model. The iterative methodology was applied to real-time data measured during dialysis, supporting subsequent development of an adaptive real-time BP estimator. Tracking of patient BP was analysed for all the subjects in the patient study, supported only by regular calibration updates from SBP cuff measurements. The methodology and associated technology was shown to be capable of tracking patient BP non-invasively via arterial line pressure measurement during complete 4-hour treatment sessions, and future refinements that were required were defined. In terms of measurement uncertainty, it was noted that when arm cuff measurements were taken in order to calibrate and update the estimation software, some of the measurements appeared to be outliers, not fitting with the trend of prediction, or trend of arterial line pressure. This impacts on the accuracy of the SBP estimator, and also would significantly impact on the accuracy of any future work developing SBP predictive software. This paper describes the development

of a real-time expert system which analyses arm cuff SBP measurements as they arrive during dialysis treatment, and acts as a decision support agent with respect to the reliability of the measurement. This methodology is shown to be tractable in real time, and to significantly improve continuous SBP estimation accuracy. Analysis of the method is presented subsequent to its deployment on 4-hour dialysis treatment sessions with the software running in real-time, moderating updates of the estimation software from the incoming arm-cuff measurements.

C. Novelty and contribution to knowledge

Blood pressure measurements can be characterised as being a reasonably accurate representation of the circumstances under which the reading is obtained. Systematic reviews have shown that a wide spectrum of circumstances can introduce large disturbances onto the baseline mean 'accurate' current state of patient blood pressure in addition to specific complicating factors introduced by HD treatment and the backdrop of a busy renal unit. Outlying measurements are often dealt with in an *ad hoc* fashion, by eliminating readings which are perceived to be out of expected range or trend, or adding extra measurements and applying averaging methods. This paper describes the novel development and application of an AI expert system based upon a physiological model and rule set, to data gathered from a separate non-invasive arterial line pressure measuring device and arm cuff measurements. The expert system identifies 'unreliable' arm cuff readings which lay outside the expected range of readings based upon the physical relationship between the relative dynamics of measured arterial line pressure and cuff measured SBP. Finally, the expert system acts as decision support, outputting a recommendation and mathematical justification for discarding or recording the most recent SBP measurement. The system requires no *a priori* knowledge of the patient's history or physiology, and has been developed to operate on the sparsely populated arm cuff measurement set as each measurement arrives. The paper contributes to knowledge associated with the fundamental relationship between arterial line pressure and underlying SBP, it highlights the number of disturbances which can occur in a typical dialysis session, and lays the foundation for accurate SBP measurement and prediction which could reliably trigger interventions to avoid the onset of hypotension during treatment.

D. Organization of this paper

II. Method

A. Intradialytic brachial cuff SBP and arterial line pressure measurements

Low-cost industrial process control pressure sensors with on-board signal amplification and linearization (Honeywell $40PC015V2A$), were integrated (fig1) with connectors to fit ports on standard dialysis lines. The connectors consist of a $4mm$ internal diameter line, a pressure transducer protector which keeps the blood side of the circuit separated from the sensor, preventing patient cross contamination with blood borne pathogens via a 0.2 micron filter. There is also a bespoke membrane barrier fitted as an extra safety precaution. Real-time data acquisition (DAQ) and storage is performed via a National Instruments NI USB-62102 16 input 16-bit, 250 kS/s multifunction I/O device. All acquisition is analogue, sampled at $1kHz$ on each measurement line. Analogue input lines operate in the range 0 to 5 V. The experimental relationship

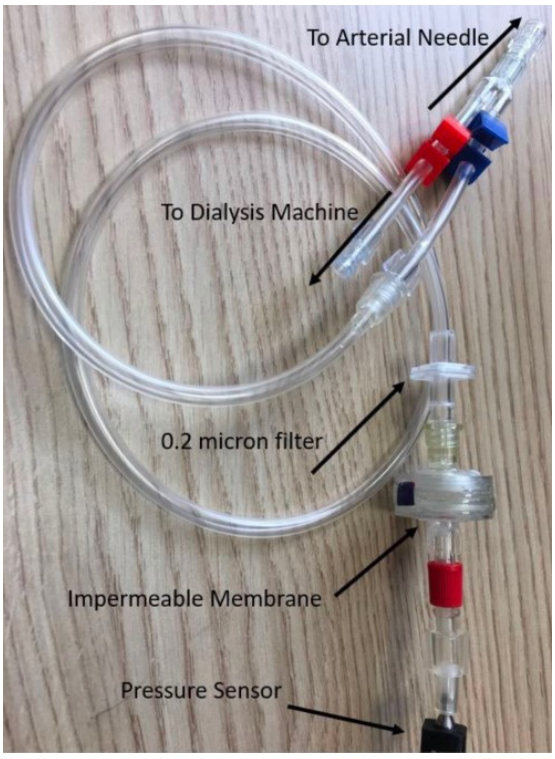

Fig. 1. Arterial line pressure sensor connector

between brachial cuff MAP and corresponding measured arterial line pressure for 11 individual $4-hour$ sessions in the patient study is shown in fig 2. A linear least squares fit of

$y = 0.8x - 1.5 * 10^2$, Root Mean Squares Error 10.3, R^2 0.615, p value 6.35×10^{-20}. As predicted, the figure displays a correlated scatter for the population around a linear least squares fit with a gradient which represents a fundamental relationship between arterial line pressure and SBP, with scatter around the fit line associated with physiological differences between patients, changes in physiology during treatment, and importantly, sources of inaccuracy in the SBP measurements. Brachial cuff SBP measurement is a steady-state measurement

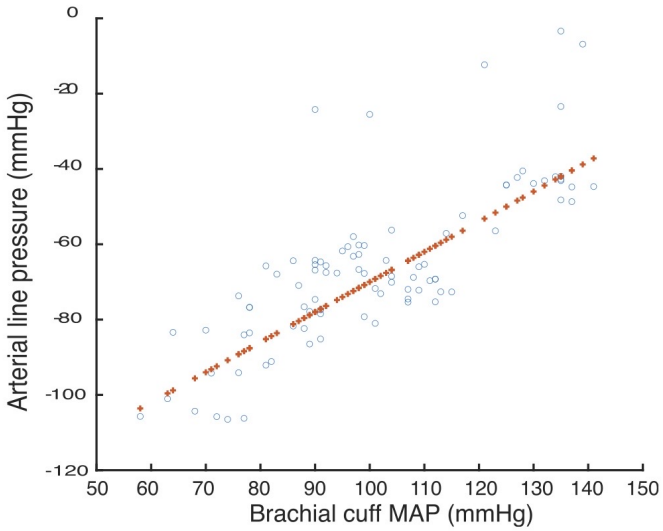

Fig. 2. Brachial cuff MAP vs Arterial line pressures in 11 patient sessions (o) with least squares linear fit (+).

'snap-shot' containing no dynamic components. In order to match this criteria, arterial line pressure at the instant of SBP measurement is captured as the output of a 5000 sample or $5s$ moving-average filter, which matches the conversion time of the dialysis machine-mounted automatic cuff measurement device. The fistula side of the arterial line needle is defined as having pressure P_1 and area A_2, while the pressure sensor is defined as having pressure P_2 and area A_2. Figure 3 depicts the arterial line - SBP measurements phase-plane captured during a typical dialysis treatment session, SBP arm cuff measurement triggers the instantaneous capture of the arterial line pressure. Linear least squares fit $f(x) = 1.0434x + 175.9$, $R^2 = 0.1137$, $RMSE = 9.871$, p value 1.4×10^{-24}, indicating that the model is significant, but doesn't account for the majority of the variation.

The phase plane relationship between arterial line pressure and cuff SBP represents a time-varying system, due to the impact of hemodialysis on the subject's physiology necessitating a time varying model (resulting in the low R^2 value for the 1st order fit in fig 3 which is derived from a static representation of the system at the end of a treatment session), with further complexity added by the presence of occasional unreliable cuff SBP measurements due to external disturbance effects. It is thus necessary to develop a model of the instantaneous relationship between cuff SBP and arterial line pressure and integrate it into a real-time time variant model. This will form the basis of a mechanism to discriminate between cuff SBP measurements.

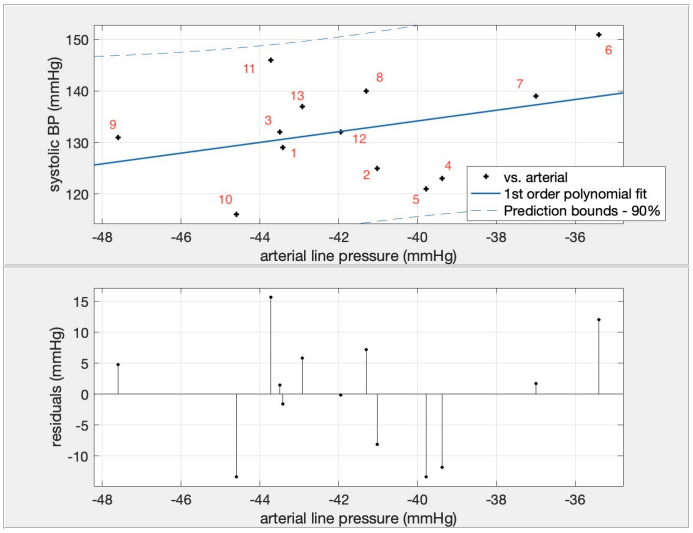

Fig. 3. Arterial line - SBP measurements phase-plane captured during a typical dialysis treatment session, numbered in order taken during session. 1st order polynomial fit applied at end of session

B. Identification of cuff SBP measurement unreliability

To develop a model of the instantaneous relationship between cuff SBP and arterial line pressure, we assume steady, incompressible flow with negligible losses, blood flow rate can be described using the Bernoulli and Continuity equations [20], where f is blood flow and R is blood density, as;

$$f = A_2 \left[\frac{2\left(P_1 - P_2\right)}{R\left(1 - \left(\frac{A_2}{A_1}\right)^2\right)} \right]^{\frac{1}{2}}. \tag{1}$$

For practical purposes of tractability, we can assume horizontal and fully developed flow at P_1 and P_2 and that blood density and viscosity are both constant during the sampling period. Further, flow rate f is defined by the blood flow rate drawn by the dialyser peristaltic pump which remains constant throughout the observational patient studies, as do areas A_1 and A_2. Consequently, eq. 1 can be simplified to;

$$f = A_2 \left[\frac{2\left(P_1 - P_2\right)}{C} \right]^{\frac{1}{2}}, \tag{2}$$

where C is a lumped parameter of the constants which can be empirically determined. Rearranging for C gives;

$$C = \frac{2\left(P_1 - P_2\right)}{\left(\frac{f}{A_2}\right)^2}. \tag{3}$$

Further, as flow f and pressure sensor area A_2 are also constants[1], combining them with C to give C' and defining

[1]In all the patient treatment sessions presented in this paper, blood pump flow is maintained at a constants set speed throughout the session. Fourier analysis of the data from a pressure sensor attached to the venous line allows continuous calculation and monitoring of flow rate enabling compensation if any flow rate changes were to occur..

P_b as measured brachial SBP gives;

$$P_b = P_2 + C^{'}, \tag{4}$$

which implies that gradient through the measurement point is positive and an offset of $C^{'}$ which is only valid at every cuff measurement. Hence, we can obtain a valid approximation of the changing relationship between the two variables by a linear polynomial fit of the form $y = \beta_0 + \beta 1x + \epsilon$ on the growing number of measured points as they are measured.

C. Expert system

An expert system is a computer algorithm which emulates the decision-making ability of a human expert, and is designed to solve problems by reasoning through bodies of knowledge, in this case *if–then rules* rather than through conventional procedural algorithms. Rule based expert systems (ES) typically contain a knowledge (rule) base, inference engine, data acquisition, decision support and user interface. Expert systems are designed to emulate an expert in a specialised knowledge domain such as clinical medicine. In the case under consideration in this paper, observation of staff on renal units reveals a 'learned skill set' when taking cuff BP measurements, with regards to excluding measurements, taking additional measurements and averaging measurements in order to get a fairly accurate estimation of BP trajectory. The expert system implementation described here draws on a coherent set of rules which combine to provide decision support regarding the reliability of cuff SBP measurements as they are taken. The expert system bases its decision making upon the effect of a new incoming measured SBP - arterial pressure data point on the current model, and whether its inclusion would be supported or excluded by the rule base. Each treatment session starts with 3 cuff measurements taken 5 minutes apart to provide the initial fit for the linear model. As each subsequent measurement is taken (generally $20 - 30mins$), it is added to the existing data set and a new linear fit calculated. The following calculations and rules are then applied in the ES software:

- acquire new SBP-arterial line pressure measurement
- add new point to existing measurements
- calculate new gradient
- Rule 1: if fitted SBP-arterial line gradient $-ve$ then reject new data point
- Rule 2: if fitted SBP-arterial line gradient ≤ 0.2 then reject new data point
- calculate residual of new point from new fit equation
- Rule 3: if residual $\geq 8mmHg$ then reject new data point
- calculate R^2
- Rule 4: if $R^2 \leq 0.1$ then reject new data point

1) Rule base discussion: The rule base is constructed from the strictures of derived mathematics describing the physical system, in addition to empirical observations from previous studies:

- Derivation of Rule 1: from eq 4, the gradient at any measurement point is positive. Consequently, a linear first order least-squares approximation to existing measured data with gradient (m) calculation of the form

$$m = \frac{N\sum(xy) - (\sum x \sum y)}{N\sum(x^2) - (\sum x)^2} \tag{5}$$

  (where N is the number of measurements) should exhibit a $+ve$ gradient. Any new data which results in m taking a negative value should thus be excluded.
- Derivation of Rule 2: eq 4 *implies* empirical evidence from cohort studies and lab based cardiovascular simulator, suggest that gradients ≤ 0.2 are not observed with reliable measurements.
- residuals $\geq 8mmHg$ have been found to be associated with unreliable measurements, i.e. in the time domain - large jumps in SBP which are not correlated with arterial pressure changes.
- $R^2 \leq 0.1$ indicates that the independent variable is not contributing enough to the variation of the dependent variable - regardless of the variable significance.

2) Application of the real-time expert system: The expert system was run in real time on 12, typically 4-hour, dialysis treatments. The data acquisition and expert system rig is shown in fig 4. The laptop is running the data acquisition software

Fig. 4. Data acquisition and expert system in situ prior to patient study session.

which is implemented under Matlab as a Simulink model which performs data acquisition from the arterial and venous line sensors via a National Instruments USB Data Aquisition Device under a NiDAQ device driver. The Simulink model also receives user inputs, such as SBP cuff measurement data when it becomes available, and provides visual real time displays of arterial, venous line pressures, cuff measurements, continuous estimated SBP. A separate Matlab programme is an implementation of the expert system, which receives new SBP/Arterial line pressure data points as they arrive, and outputs decision support as to whether the new cuff reading is reliable. Based on this evidence the user includes/excludes the new data point from updating the continuous SBP estimator software.

Computing/Algorithms/Software Mathworks Matlab/Simulink software on laptop performs (fig 5) the following algorithms over 4-hour treatment sessions:

- Continuous real-time data acquisition from arterial and venous sensors
- Arm cuff BP calibration data acquisition
- Real-time display of sampled systolic, diastolic arm cuff data
- Real-time display of arterial and venous line pressure
- Real-time display of blood pump flow rate
- Identification of unreliable arm cuff measurements
- Real-time continuous display of estimated blood pressure
- Storage of post-treatment data
- Predictive BP data

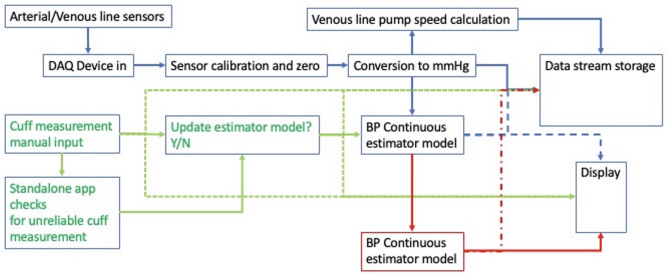

Fig. 5. Data acquisition, processing and display flowchart

Fig 3 showed an unprocessed data set from one of the study sessions, and the order in which the measurements arrived, this session will be used in this section to provide graphical examples from the data processing as it proceeds in real-time. Fig 6 shows the accepted/rejected measurements at the end of the session, with the final polynomial fit and 90% prediction bounds. Of interest is that one of the accepted data points exhibits a residual $> 10mmHg$ whereas the expert system should reject residuals $> 8mmHg$. Examination of fig 7 reveals the motion of the current least squares fit line in the phase plane as new accepted data points are added. It can be seen that due to the motion of the phase plane vector, data points (for example data point 2, fig 3) will be accepted relative to the current linear fit, but may appear to be outside specification constraints when reviewing the entire time series.

3) Review of study session data: In all treatment studies, the first three cuff measurements at the start of treatment and taken approx. 5-minutes apart are accepted as they form the foundation of the development of the phase vector's trajectory and are the minimum number of measurements necessary to calculate a least squares fit. If, however this produces a negative gradient, the algorithm accepts two of the points which together give a positive gradient. In the study session presented here, 13 arm cuff measurements were taken over a 3.9 hour treatment period. Of the 13 measurements taken, measurements $|4\ 5\ 10\ 11|$ were recommended for exclusion by the algorithm. Data points $|4\ 5|$ on the basis of $-ve$ gradient, data points $|10\ 11|$ on the basis of large residual from linear fit. Consequently the phase vectors displayed in fig 7 represent a time-series of accepted points $|6\ 7\ 8\ 9\ 12\ 13|$. Points$|1\ 2\ 3|$ are incorporated with point 6. We can now move from the pressure-domain to the time-domain shown for this patient's session in fig 8. Shown in the graph are SBP cuff measurement data points separated into accepted and excluded

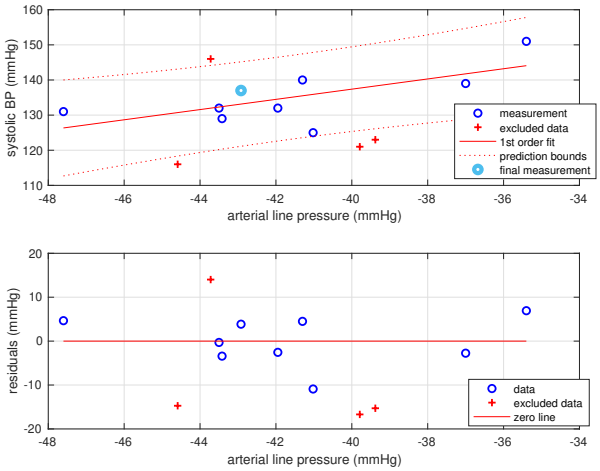

Fig. 6. Accept/reject phase plane, 1st order polynomial fit and residuals associated with patient session depicted in fig 3, calculated in real-time during treatment session. Prediction bounds $\mathbf{90\%}$

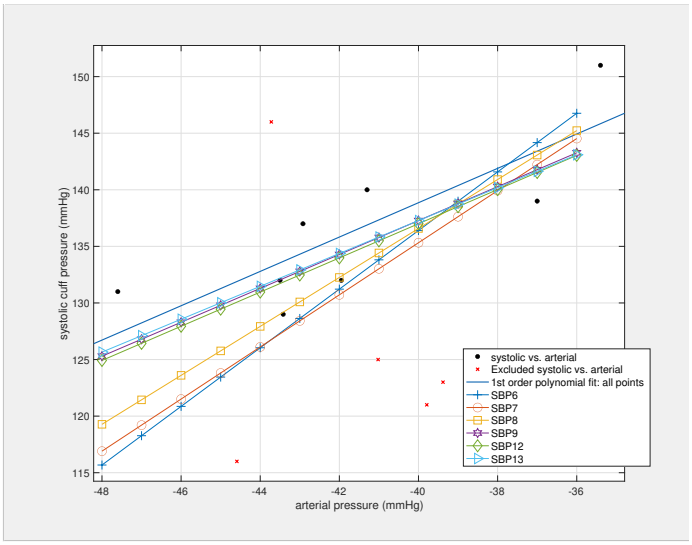

Fig. 7. SBP - Arterial line model developing over time as new arm cuff measurements become available.

measurements. Continuously measured arterial line pressure, and estimated continuous SBP are also shown. Continuous SBP calculations [14], [15] are updated only by accepted SBP cuff measurements.

Data points $|1\ 2\ 3|$ taken at 5-minute intervals form the foundational basis of the phase plane model and initial calibration of the SBP estimator. New SBP cuff data points $|4\ 5|$ present falls of $9mmHg$ and a further $2mmHg$ and subsequently an increase of $30mmHg$ to SBP cuff data point 6, none of which correlates with proportional rises or falls in arterial BP. The expert system recommends the exclusion of data points $|4\ 5|$, no estimator calibration takes place, and we can assess the quality of the exclusion by comparing the estimated systolic pressure (based upon the update at data point 3) at data point 6, with the actual measured cuff SBP at the same datapoint. The predictor blood pressure was shown to rise prior to the cuff measure, which then came in with a small error (6.6mmHg).

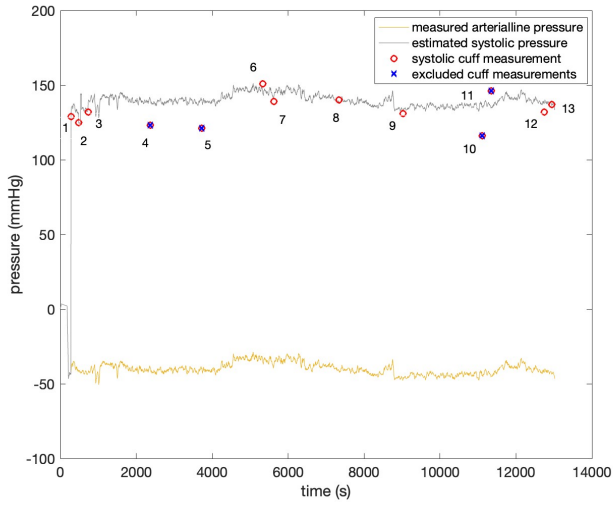

Fig. 8. Representative dialysis session data, showing arterial line pressure measurement, SBP real-time estimation, accepted and excluded SBP arm cuff measurements

This suggests that the estimator was correct in disregarding the two previous cuff measurements. Subsequent accepted SBP cuff measurements $|7\ 8\ 9|$ were associated with estimation errors of $3.9,\ 1.41,\ 1.2\ mmHg$ respectively. The expert system recommended the exclusion of data points $|10\ 11|$ which represented a drop of $15mmHg$ from data point 9 and a subsequent rapid rise of $30mmHg$. The model from data point 9 was not updated, and consequently estimation errors at points $|12\ 13|$ were $6.0,\ 0\ mmHg$ respectively. The continuous SBP estimation errors are shown in table I and are based upon the exclusion of cuff measurements $|4\ 5\ 10\ 11|$ as previously described, resulting in a mean estimation error of $4.24mmHg$.

TABLE I
SBP CONTINUOUS ESTIMATE ($\boldsymbol{mmHg}$). MEAN ERROR **4.24**, MAX ERROR **6.8**, MIN ERROR **0**

Measurement	Cuff SBP	Estimate	Error
1	129	135	6
2	125	131.3	6.3
3	132	138.8	6.8
4	n/a	n/a	n/a
5	n/a	n/a	n/a
6	151	144.4	6.6
7	139	142.9	3.9
8	140	138.59	1.41
9	131	132.2	1.2
10	n/a	n/a	n/a
11	n/a	n/a	n/a
12	132	138	6
13	137	137	0

4) Discussion: In a healthcare setting, accurate BP is relied on to identify clinical deterioration and guide goal-oriented treatment. Additionally, non-invasive continuous BP estimators can self-calibrate with arm cuff SBP measurements during treatment gaining estimation robustness against physiological changes during dialysis [14]–[17]. Finally, emerging applications of AI to the important goal of accurately predicting in real-time both hypo- and hyper- tension will benefit immensely from accurate and reliable SBP measurements [18], [19] Regarding the errors observed between estimated and measured SBP when accepted cuff measurements are taken, as derived earlier in this paper, (4), we can express the relationship between estimated continuous SBP and areterial line pressure at the previous measurement point as;

$$P_{b(t0)} = P_{2(t0)} + C'_{(t0)}, \tag{6}$$

where $P_{b(t0)}$ represents estimated SBP cuff, $P_{2(t0)}$ is arterial line pressure, and $C'_{(t0)}$ is the system transfer model, all at t_0 the previous SBP cuff measurement event and forms the continuous SBP estimator until time t_n. Similarly, we can express the relationship between measured cuff SBP and arterial line pressure at the current measurement event as

$$P_{b(tn)} = P_{2(tn)} + C'_{(tn)}, \tag{7}$$

where t_n the time of the current SBP cuff measurement event. If we assume that time t_0 precedes t_n by a time period which is an order of magnitude smaller than the fastest time constant to be experienced in the system (i.e. $(120bpm = 0.5s/10 = 0.05s)$, we can assume

$$P_{b(t0)} = P_{b(tn)}, \tag{8}$$

is valid (as assumed in Tables (I,II). Hence,

$$P_{2(tn)} = P_{2(t0)} + (C'_{(t0)} - C'_{(tn)}). \tag{9}$$

Representing $(C'_{(t0)} - C'_{(tn)})$ by δC and substituting into eq (7) yields the expression

$$P_{b(tn)} = P_{2(t0)} + C'_{(tn)} + \delta C. \tag{10}$$

Thus, the prediction error between the predictor based upon the last system model and the updated model obtained when the new arm cuff measurement is obtained is directly related to the difference between the current system model and the model obtained at the last arm cuff measurement. The results shown in Tables (I,II) are subsequent to the exclusion of SBP cuff measurements which are categorised as outliers. The results shown for a patient session in Table (I) have a maximum error of $6.8mmHg$ which are associated with changes in physiology between model updates at SBP cuff measurements. The excluded measurements would contribute a mean error of $16.71mmHg$ and max error $19.4mmHg$, and hence the exclusion decisions taken by the expert system are valid. It is worth noting that we can assume that model error is closely associated to arm cuff measurement frequency which is, in practical terms, closely associated with, and limited by, the patient experience

III. RESULTS

The system was run in real time during 12, typically 4-hour patient dialysis sessions, giving overall estimation performance of $6.125mmHg$ mean error, $13.29mmHg$ mean maximum error and $0.844mmHg$ mean minimum error across all the SBP cuff measurements in the entire study. Performance data

TABLE II
OBSERVATIONAL STUDY OF 12 PATIENT TREATMENT SESSIONS: SBP PREDICTION ESTIMATE ($mmHg$).

Session	Mean Error	Max Error	Min Error
1	7.75	10.2	2
2	2.38	3.6	0.4
3	9.67	21	0.94
4	6.04	10.13	3.67
5	5.37	15.8	0
6	5.013	15.81	0.04
7	8.56	19	1
8	8.45	17.7	0
9	4.24	6.8	0
10	3.84	8.8	0.32
11	7.06	13.92	0.762
12	5.126	16.75	1

for individual sessions in the study is given in table II. It is worth noting that this performance is delivered by an expert system based around a very small number of rules, and there still exist opportunity to deal with 'edge case' measurements with a more complex set of rules, which will be developed in further work and observational studies.

Fig 9 shows the time domain data from observational study no.8, consisting of 14 SBP cuff measurements taken over a 4.2-hour treatment session. It is likely that cuff measurement 4 would have been identified as unreliable without decision support, as it is such a large drop in SBP between readings, and also was identified correctly by the algorithm. Also possible would have been the identification of measurement 11 as being potentially unreliable due to the sudden large rise in BP after a steady downward trend. In this case, the expert system correctly associates the rise in SBP cuff with a rise in arterial pressure, and accepts the reading. Measurement 12 might possibly have been accepted, but in this case the expert system correctly identifies that arterial line pressure has dropped since the previous reading, and correctly suggests 'exclude' for data point 12.

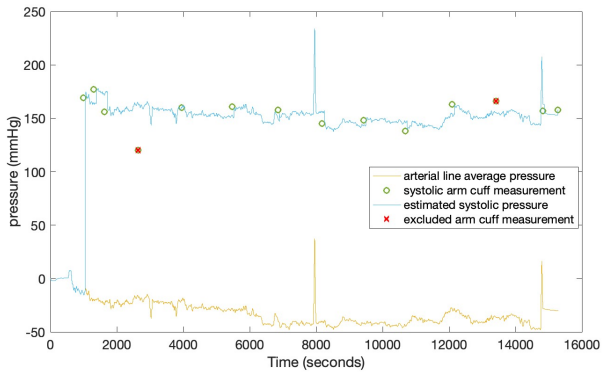

Fig. 9. Representative time domain data from patient study session 8.

IV. CONCLUSION

When SBP cuff measurements are taken during a dialysis treatment session, the staff member conducting the data collection will often apply *ad-hoc* rules to sort valid from non valid measurement. In the case of perceived unreliability in the measurements, extra measurements may be taken, and some method of averaging may be applied. In order to develop reliable SBP prediction, reliable SBP cuff measurements and preferably reliable continuous SBP estimates are critical. The methodology presented here identifies and separates reliable from unreliable data. In this application area, the unreliable measurements are not necessarily 'wrong', but may represent disturbances which have been outlined in a variety of systematic reviews of SBP cuff reliability. There are important observations to be made regarding the effectiveness of the approach presented here. Firstly, in the treatment example session (fig 8) examined in this paper 13 measurement points is an extremely sparse set of data upon which to base decisions. Furthermore, this data set is only available in full at the end of the session, so decision making is based upon the existing measurements which can be as few as 3. It's relatively simple (sometimes) to look back at the entire time series of data and pick out obvious candidates for exclusion. However, in real-time, when arm cuff measurements $[4\ 5]$ are taken, it is difficult to judge whether they indicate a trend, or are in fact not reliable indicators of the underlying patient SBP. Similarly for data points $[10,\ 11]$. The Expert System presented in this paper is based around physical models and statistics, and hence delivers justifiable, standardised output. There is no suggestion at the moment that the methodology provide anything more than decision support, but it does represent a valuable tool for dialysis unit staff. The method has the potential to improve the accuracy of BP predictor algorithms and hence more reliable identification and intervention before the onset of hypotension, which will be the subject of future work.

PATIENT STUDY

TABLE III
PARTICIPANT CHARACTERISTICS

Variable	(n=8)
Age (years)	75 (IQR 52 to 82)
Male [n (%)]	5 (63)
White ethnicity [n (%)]	6 (75)
Diabetes [n (%)]	4 (50)
Heart disease [n (%)]	1 (13)
Dialysis vintage (months)	75.5 (30 to 102)
Fistula blood flow assessment (QA)	620 (343 to 936)
Vascular access type	
Brachiocephalic arteriovenous fistula [n (%)]	5 (63)
Radiocephalic arteriovenous fistula [n (%)]	3 (37)
Needle gauge	
2x14g [n (%)]	6 (75)
2x15g [n (%)]	2 (25)
Urea (mmol/L)	18.9 (15.1 to 25.2)
Creatinine (μmol/L)	753 (544 to 903)
Potassium (mmol/L)	5.0 (4.6 to 5.6)
Phosphate (mmol/L)	1.33 (1.16 to 1.69)
Albumin (g/L)	33 (30 to 34)
Haemoglobin (g/L)	123 (113 to 126)
Post-dialysis weight (kg)	71.8 (53.0 to 88.3)
Body mass index (kg/m^2)	24.2 (22.0 to 27.4)

ETHICS APPROVAL

This study has been reviewed and given favourable opinion by the West Midlands (Coventry and Warwickshire) Research Ethics Committee (REC reference: 17/WM/0080). This study has been conducted in accordance with the ethical principles that have their origin in the Declaration of Helsinki, 1996; the principles of Good Clinical Practice, and the Department of Health Research Governance Framework for Health and Social care, 2005

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US Patent Office & Overseas License 62/855069 MEASURING PRESSURE WAVES IN DIALYSIS LINES TO DERIVE CONTINUOUS ARTERIAL BLOOD PRESSURE Prof Paul Stewart, Prof Jill Stewart, et. al. iTrend Medical Research Ltd.

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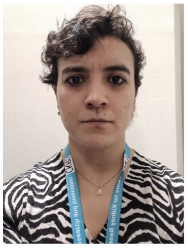
Jill Stewart received an MEng (2001) and PhD (2005) in mechanical engineering from the Wolfson School of Mechanical Engineering at the University of Loughborough UK. Since then she has held a number of academic posts including Head of School /Department at Lincoln University and Sheffield Hallam University. She is the founding Director of the Institute of Engineering, Computing and Advanced Manufacture at the University of Cumbria. Professor Jill is a Fellow of the HIgher Education Academy, a Fellow of the Institution of Mechanical Engineering and a Chartered Engineer.

Paul G. Stewart Received the BEng (1996) and PhD (2000) degrees in electronic, control and systems engineering from the Department of Automatic Control, University of Sheffield, U.K. and has held posts of Head of Aerospace Engineering at Salford University, Founding Head of Engineering and Pro Vice Chancellor Research at Lincoln University, Director of Institute for Sustainable Engineering and the Mel Morris Endowed Chair in Intelligent Systems at the University of Derby, and Founding Research Chair in Engineering and Advanced Manufacturing at the University of Cumbria. Professor Stewart is Deputy Editor in Chief of *Energies* Journal, a Fellow of the Higher Education Academy U.K., Senior Member of the Institution of Electronic and Electrical Engineering (Chairman: UK and Republic of Ireland IEEE Industrial Electronics Chapter (2009 – 2010)), Fellow of the Institution of Mechanical Engineers, and a Chartered Engineer.

Rebecca Noble is a research fellow in the Centre for Kidney Research and Innovation (CKRi) in Royal Derby Hospital as a research fellow, previously in the Precision Imaging Beacon at the University of Nottingham. She graduated from The University of Nottingham receiving a Bachelor of Medicine Bachelor of Surgery (2012) and BMedSci (2010), and achieved Membership to the Royal College of Physicians London and a Postgraduate Certificate in Medical Education with Distinction. Dr Noble's has a particular interest in mutliparametric MRI and has maintained links with the renal imaging group at The Sir Peter Mansfield Imaging Centre (SPMIC). As well as work in AKI, Dr Noble has also collaborated with SPMIC with work developing sodium MRI and evaluating the impact of dialysis on whole organ sodium levels. Currently Dr Noble is working towards a PhD with the University of Nottingham.



Daniela Viramontes-Hörner graduated with honours from the BSc Nutrition and Dietetics, University of Guadalajara, Mexico in 2009, graduated with distinction from the MRes Dietetics, University of Nottingham in 2015, and was awarded PhD in the Centre for Kidney Research and Innovation, University of Nottingham in 2019. Dr. Viramontes-Hörner worked (2011-2014) for a Mexican company (developing nutritional products for people with kidney disease) in the innovation, research and development department leading randomised controlled clinical trials related with the effect of symbiotics on gastrointestinal symptoms, nutritional status, inflammation and kidney function in people with chronic kidney disease not on dialysis, as well as in people receiving haemodialysis. She is currently, a research fellow (level 4) working in the Centre for Kidney Research and Innovation, Academic Unit for Translational Medical Sciences, School of Medicine, University of Nottingham UK.

Maarten W. Taal received an MBChB in 1987 and MMed in 1997 from the University of Cape Town Medical School, South Africa. After completing his post-graduate training in nephrology at Groote Schuur Hospital, Cape Town, he joined the Laboratory of Kidney and Electrolyte Physiology at Brigham and Women's Hospital, Boston, USA under the directorship of Barry M. Brenner, MD. His research focused on mechanisms underlying the progression of chronic kidney disease and earned him a Doctor of Medicine degree from the University of Cape Town in 2003.He subsequently moved to the United Kingdom where he was appointed a Consultant Renal Physician at Derby City General Hospital (now Royal Derby Hospital) in 2002 and Honorary Associate Professor at the University of Nottingham in 2011. He was appointed Professor of Medicine at the University on Nottingham in 2014, where he leads the Centre for Kidney Research and Innovation and was appointed Director of the Academic Unit for Translational Medical Sciences in 2021. He serves as an Editor for "Brenner and Rector's The Kidney", Section Editor for "Current Opinion in Nephrology and Hypertension" and Academic Editor for "PLOS Medicine". He is a Past President of the British Renal Society and current Chair of the International Network of CKD Cohorts (research committee of the International Society of Nephrology).Prof Taal is a Fellow of the Royal College of Physicians and a Fellow of the Association of Physicians of Great Britain and Ireland.

Micholas M. Selby studied medicine at the University of Nottingham, UK, graduating in 1998, and was appointed a full-time NHS consultant nephrologist at the Royal Derby Hospital in 2009. In 2015 he was appointed Associate Professor of Nephrology at the University of Nottingham, based in the Centre for Kidney Research and Innovation (www.nottingham.ac.uk/research/groups/renal; Twitter:@CKRIresearch), Royal Derby Hospital Postgraduate Medical School; in March 2020 he was awarded a personal chair. Prof. Selby is a clinical academic with primary interests in Acute Kidney Injury (AKI), Magnetic Resonance Imaging (MRI) of the kidney and the haemodynamic consequences of dialysis. He led the development of one of the first e-alert systems for AKI in the UK and is CI on several investigator-instigated studies in these areas including AFiRM and MOSAICC. Prof Selby has been awarded peer-reviewed grant funding from NIHR, MRC, the Health Foundation, Kidney Research UK and British Renal Society, and has published over 100 peer-reviewed articles. Prof Selby has several national and international AKI roles, including immediate past chair of the AKI Clinical Study Group and UK Renal Imaging Network that sit within the UK Kidney Research Consortium and the ERA-EDTA Nephrology and Public Policy Committee for AKI. He is currently clinical lead for the Department of Renal Medicine at University Hospitals of Derby and Burton NHS Foundation Trust.