

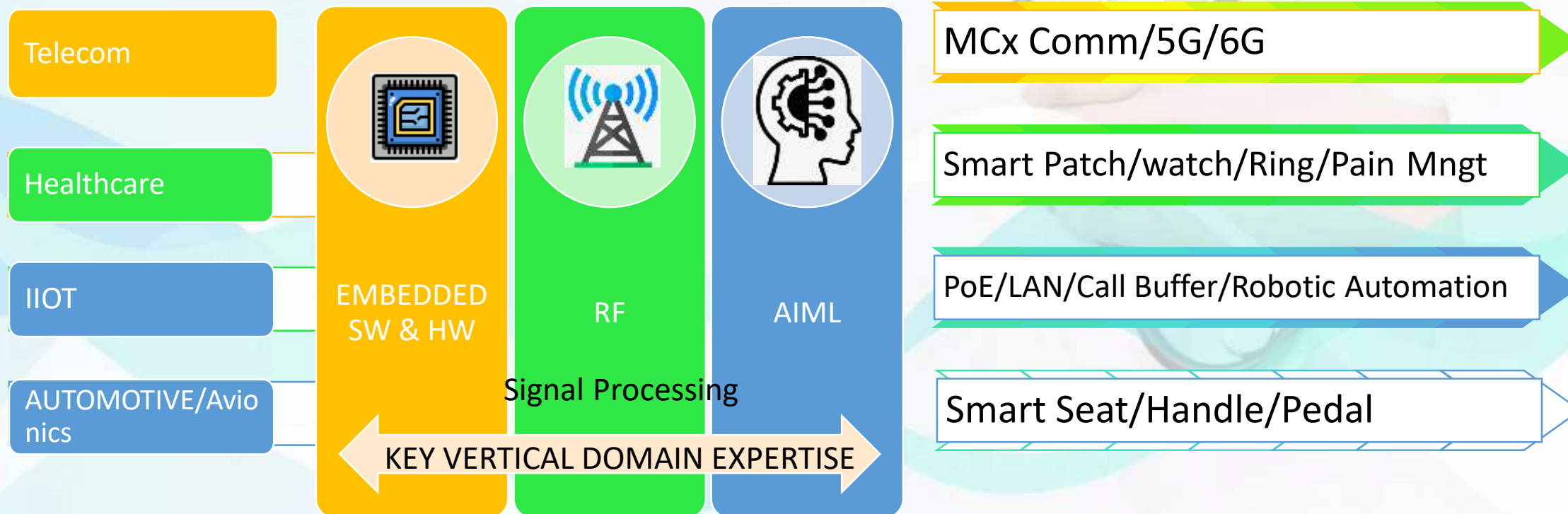
Health Monitoring System and Opportunities

Agenda

- Introduction to Asmaitha
- Health Monitoring and IoT
- Global health Market in IoT space
- Gaps and Opportunities
- What we offer in HealthCare
- Customers
- Road Map
- Asmaitha Algorithms and Patents

Introduction to Asmaitha

- 14yrs young innovation company
- Avg age is ~28 yrs

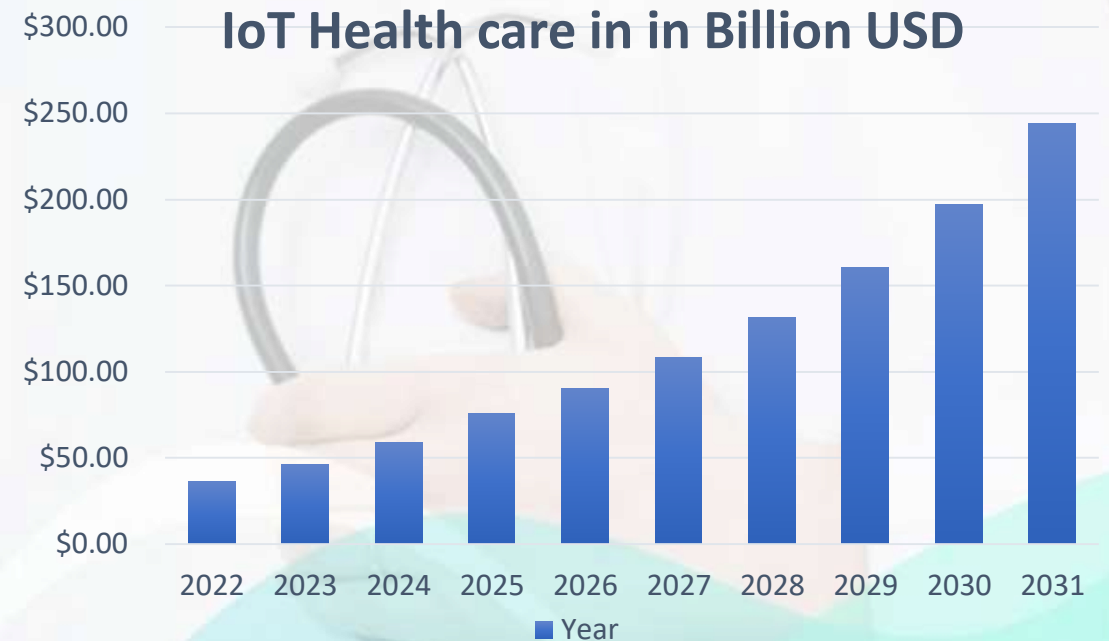


Introduction to Asmaitha



Global health Market in IoT Space

- Reasons for Health Monitoring
 - Post covid
 - Health Insurance cost
 - Govt focus to reduce mortality using early detection
 - Well being as opportunity
- Growth Projection
 - The global IoT Healthcare market size surpassed USD 36.20 billion by 2022
 - Project market size is USD 300 billion by 2032
 - Projected market size growth at 23.4% CAGR



Gaps and Opportunities

- Intimate and non invasive
- Continuous, wireless monitoring
- Diagnosis
- Treat and track
- Post operational cost
- Life style changes

What Asmaitha offer in Healthcare



Teen offering:

- Early health detection
- Stress Monitoring
- Anxiety Monitoring
- Activity monitoring
- Adolescence monitoring



Working age group can relax



Golden age:

- Remote Monitoring by their Children
- Blood pressure monitoring
- Aadhar based health monitoring
- Respiratory solution



SAAS based solution

- “SAAS based solution for real-time Monitoring of Vital parameters”
- Mission:-

To provide real-time vital measurement and analysis to Patch/device vendors, Chipset vendors, Home-health care solution providers.

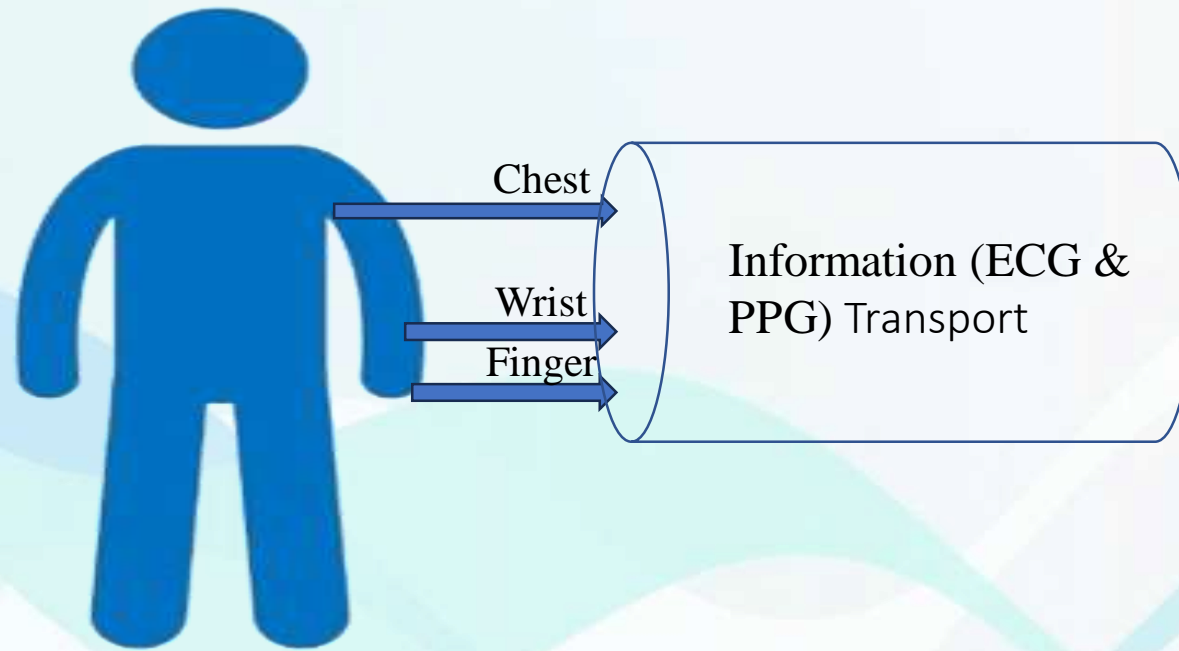
Problem Statement

- BP Accuracy for real-time monitoring using wearables, Patches, holsters ..etc. is a challenge
- Limitation in the processing capabilities of the wearable devices to provide accurate BP
- Realtime Digital signal processing of the PPG and ECG data is a limitation in wearable devices
- Non-invasive blood pressure monitors often suffer from data inaccuracies due to external factors like movement, skin type, Skin color, wrist size, emotions, ambient environment ..etc.
- Non-invasive blood pressure monitors often depend on specific body sites for data collection, limiting their flexibility and convenience
- Non-invasive blood pressure monitors often depend on specific signal characteristics, such as wavelength, which can limit their flexibility and accuracy.
- Current non-invasive blood pressure monitors are limited by their reliance on specific light wavelengths (e.g., red, infrared, green), which can restrict flexibility and accuracy.
- Traditional ECG signals are complex and challenging to analyze, making it difficult to diagnose a wide range of heart diseases accurately.

Solution Statement

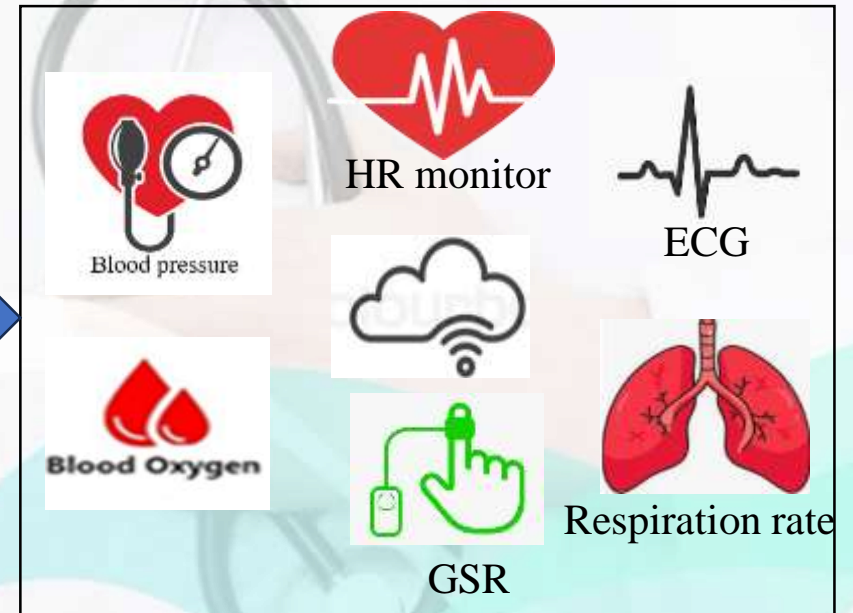
- Using powerful machine learning and AI models, we can analyze PPG and ECG data for accurate and efficient blood pressure monitoring. Cloud-based platforms provide the computational power and scalability to handle complex algorithms and large datasets, overcoming wearable device limitations and enhancing measurement reliability.
- Leveraging cloud-based platforms enables the use of powerful machine learning and AI models for data analysis, providing real-time and precise blood pressure monitoring. This approach enhances the efficiency and reliability of measurements.
- Cloud-based solutions offer scalable, high-performance computing resources, enabling real-time digital signal processing. Pay-as-you-go models make these solutions cost-effective and globally accessible.
- Implementing advanced algorithms and machine learning and AI techniques to filter and compensate for noise and variability can improve data accuracy. Real-time adjustments based on detected motion or skin type variations can further refine measurements.
- Developing a site-independent system that can take ECG and PPG data from the wrist, chest, or finger ensures versatility and ease of use. This flexibility allows for continuous monitoring regardless of the device's location on the body.
- Developing a wavelength-independent system using advanced algorithms and adaptive signal processing techniques ensures accurate measurement of blood pressure and heart rate from signals like ECG and PPG, regardless of the light color used. This approach enhances versatility and reliability.
- Utilize AI and machine learning models to analyze ECG signals more efficiently. These advanced models can identify patterns and anomalies, enabling the detection of over 200 different heart conditions with greater accuracy. This approach enhances diagnostic precision and supports early detection and management of cardiovascular diseases.

Bp algorithm Signal acquisition

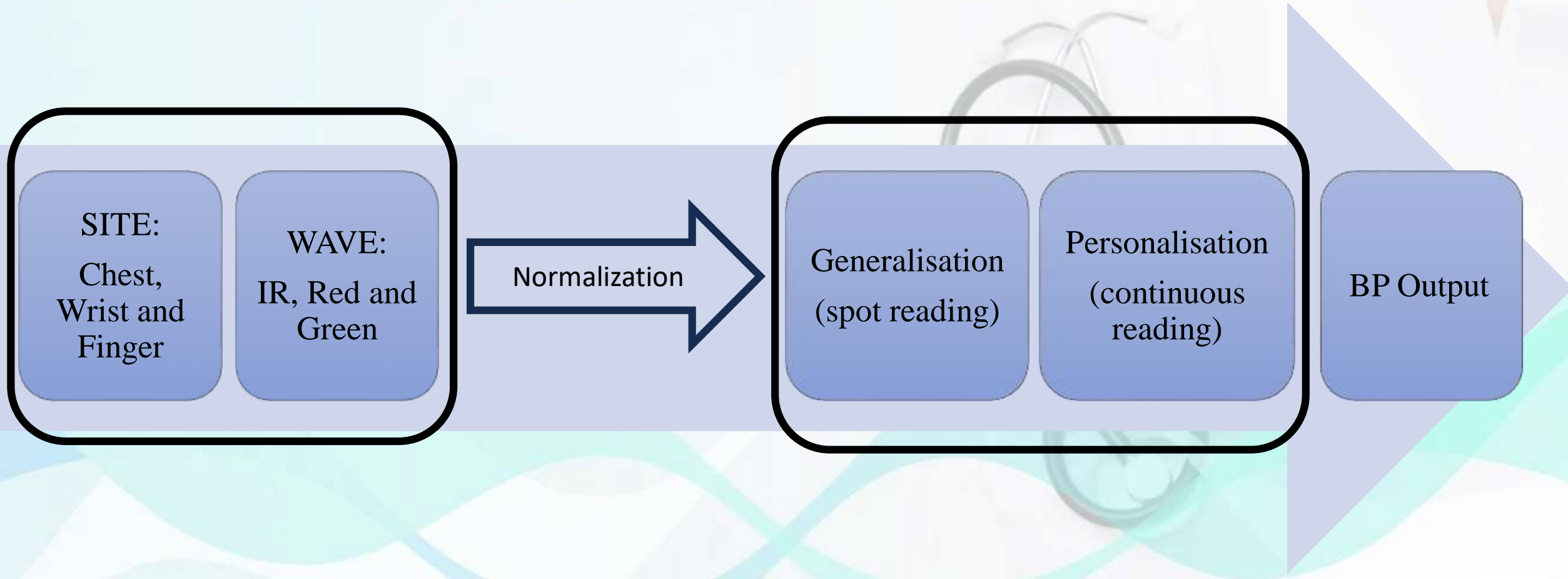


Non-Invasive Vital Collection

Gen AI Assisted BHOER SaaS Platform



BP Algorithm flow



BP Algorithm flow



SUMMARY

	No. of Measurements	No. of beats in million	Range in mmHg	Mean Absolute Deviation(MAD in mmHg)	
SBP	28561	1.2 M	<120mmHg	4.019978	3.917271
			120mmHg-139mmHg	2.882649	
			140mmHg-160mmHg	2.290621	
DBP	28561	1.2 M	<80mmHg	3.88704	3.046627
			80mmHg-89mmHg	2.188553	
			90mmHg - 100mmHg	3.002575	

Accuracy Table

Health Care Customers

Chest Patch



Medical Grade



RPM Vendors



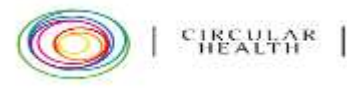
Home Devices



Wrist Watch



Ring



Ear Pod



Patents Filed and in process

- ECG based algorithm/method to detect arrhythmia
- Non invasive Blood pressure monitoring method/algorithm
- Respiratory device with warning alert mechanism

BP Algorithm Chest Data (continuous) Results- 8 Users

SBP : 90 – 160, DBP: 60 - 110

m	No. of Measurements	No. of beats	Range in mmHg	Mean Absolute Deviation(MAD in mmHg)	
SBP	25000	1M	<120mmHg	1.5513	1.3725
			120mmHg - 139mmHg	1.2306	
			140mmHg- 160mmHg	1.3356	
DBP	25000	1M	<80mmHg	0.7656	0.745
			80mmHg - 89mmHg	0.5009	
			90mmHg - 100mmHg	0.9685	

Accuracy Table

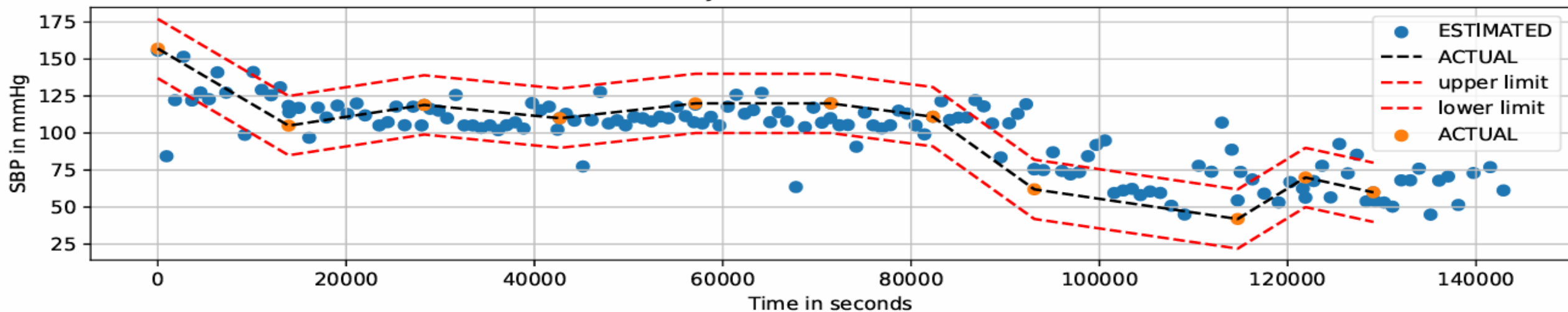
Person 1 (No. of MSRID's: 11)

Systolic Blood Pressure (MAE: 5.02) (Min diff: 0.0) (Max diff: 13.64)

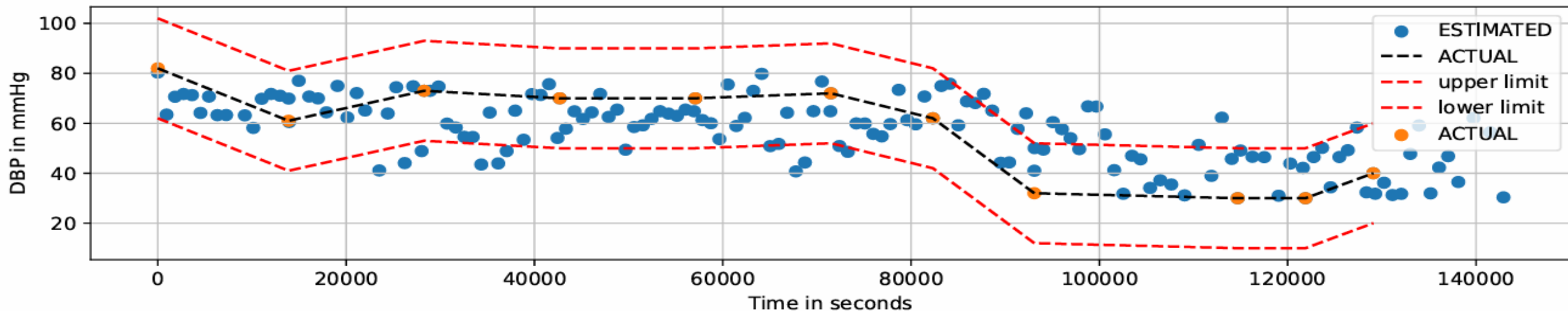
Diastolic Blood Pressure (MAE: 1.78) (Min diff: 0.0) (Max diff: 9.0)

Continuous 48 hours of data recorded every 15 minutes

Systolic Blood Pressure



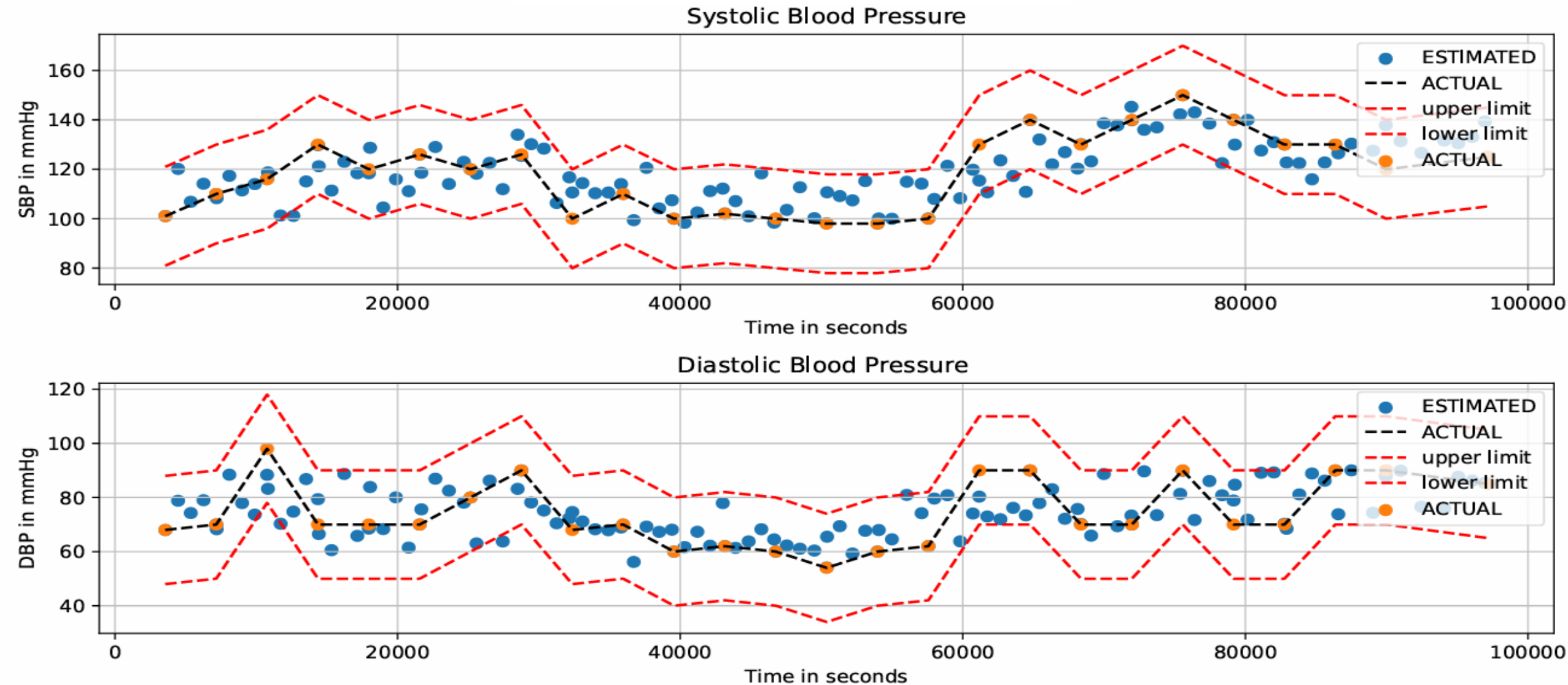
Diastolic Blood Pressure



Person 2 (No. of MSRID's: 26)

Systolic Blood Pressure (MAE: 1.11) (Min diff: 0.01) (Max diff: 14.58)

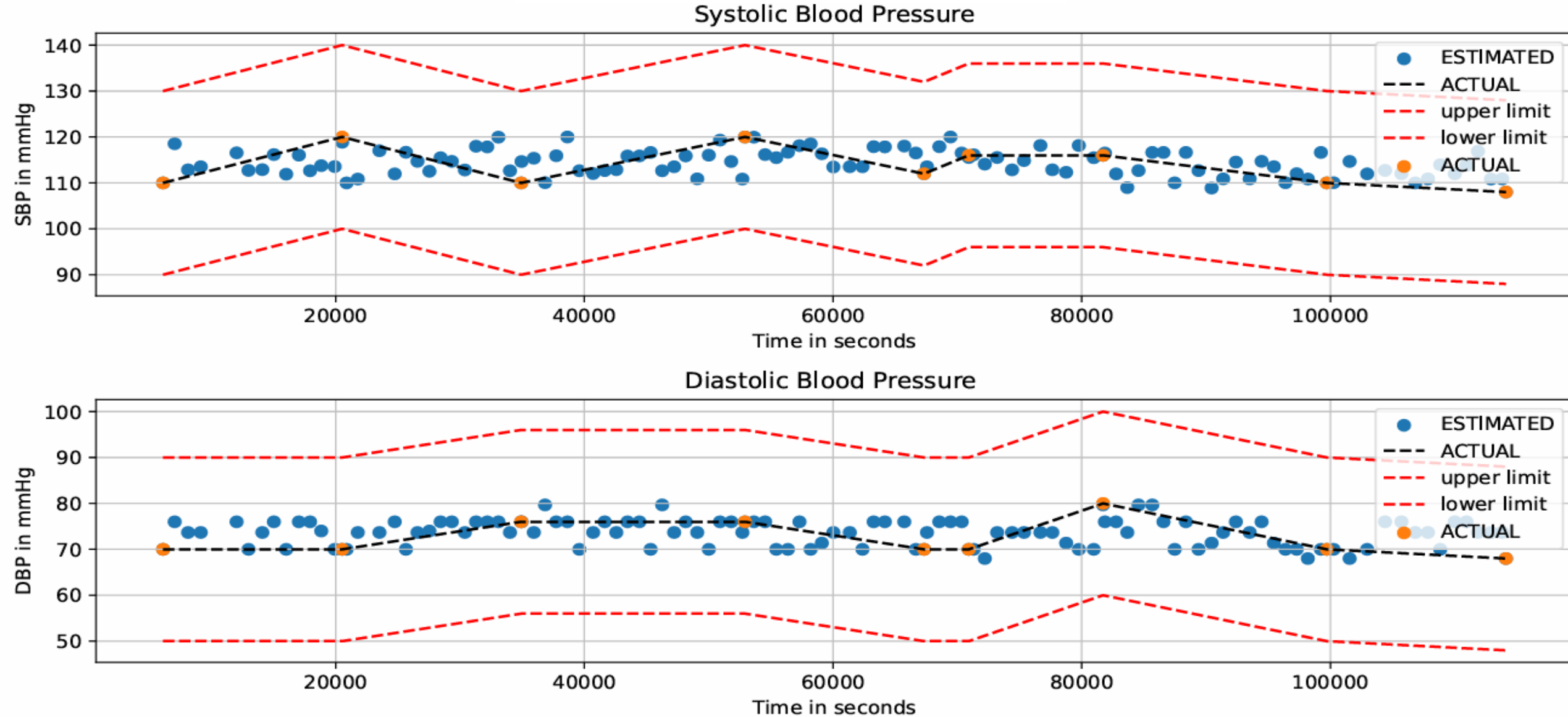
Diastolic Blood Pressure (MAE: 1.79) (Min diff: 0.0) (Max diff: 9.68)



Person 3 (No. of MSRID's: 9)

Systolic Blood Pressure (MAE: 0.18) (Min diff: 0.0) (Max diff: 1.14)

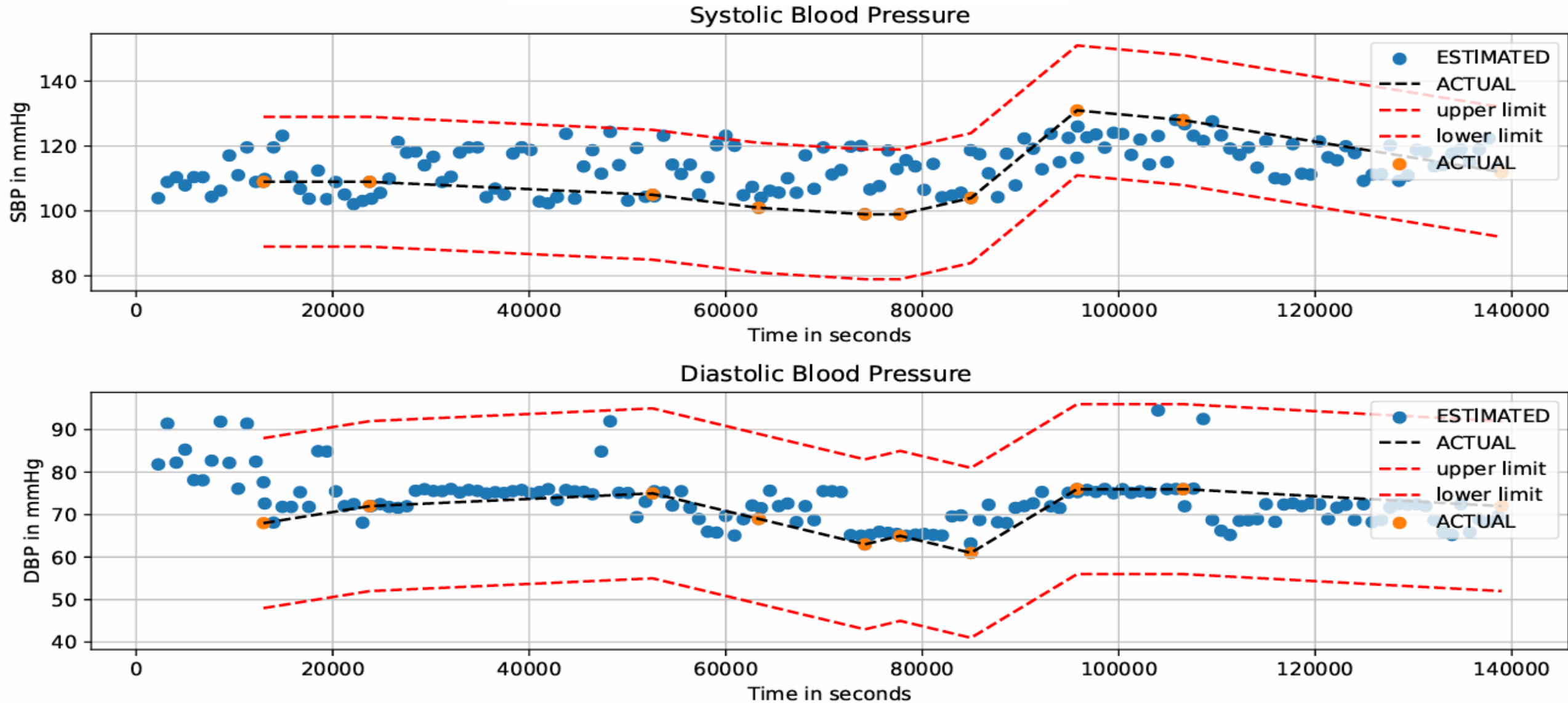
Diastolic Blood Pressure (MAE: 0.04) (Min diff: 0.0) (Max diff: 0.32)



Person 4 (No. of MSRID's: 10)

Systolic Blood Pressure (MAE: 1.46) (Min diff: 0.0) (Max diff: 14.59)

Diastolic Blood Pressure (MAE: 0.96) (Min diff: 0.0) (Max diff: 9.62)

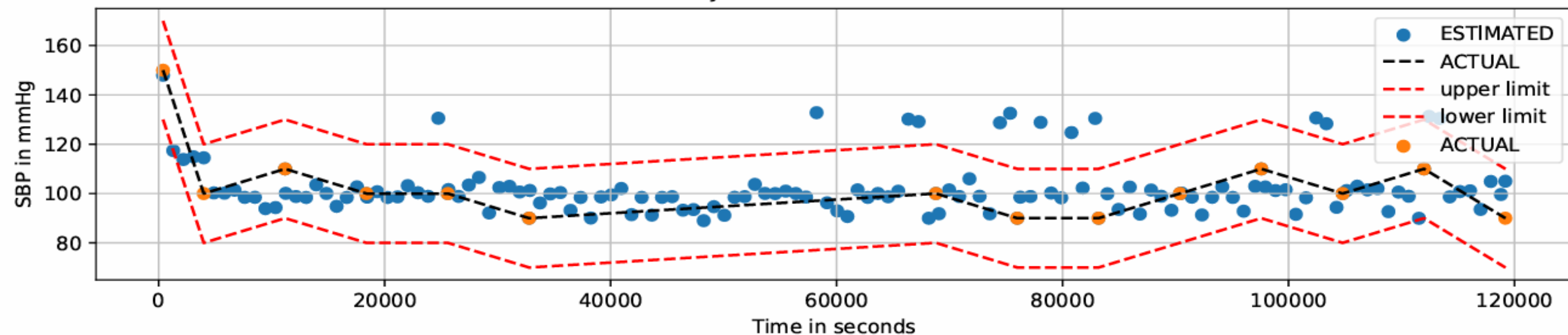


Person 5 (No. of MSRID's: 14)

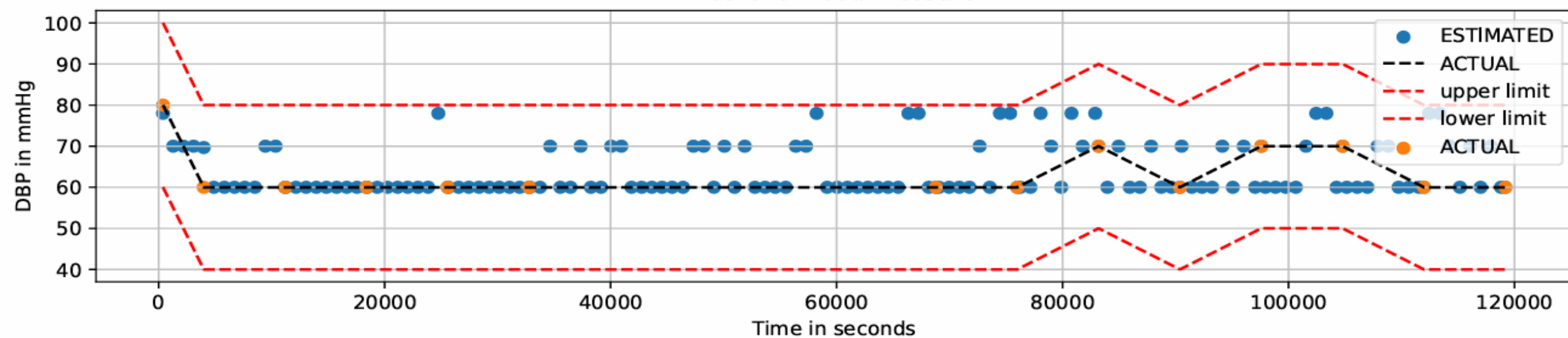
Systolic Blood Pressure (MAE: 2.26) (Min diff: 0.0) (Max diff: 15.0)

Diastolic Blood Pressure (MAE: 0.83) (Min diff: 0.0) (Max diff: 9.67)

Systolic Blood Pressure



Diastolic Blood Pressure

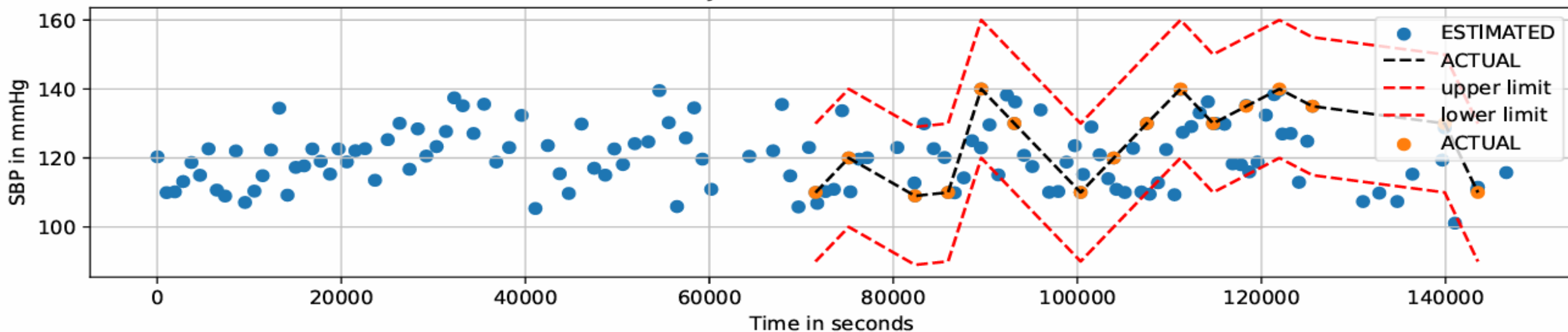


Person 6 (No. of MSRID's: 16)

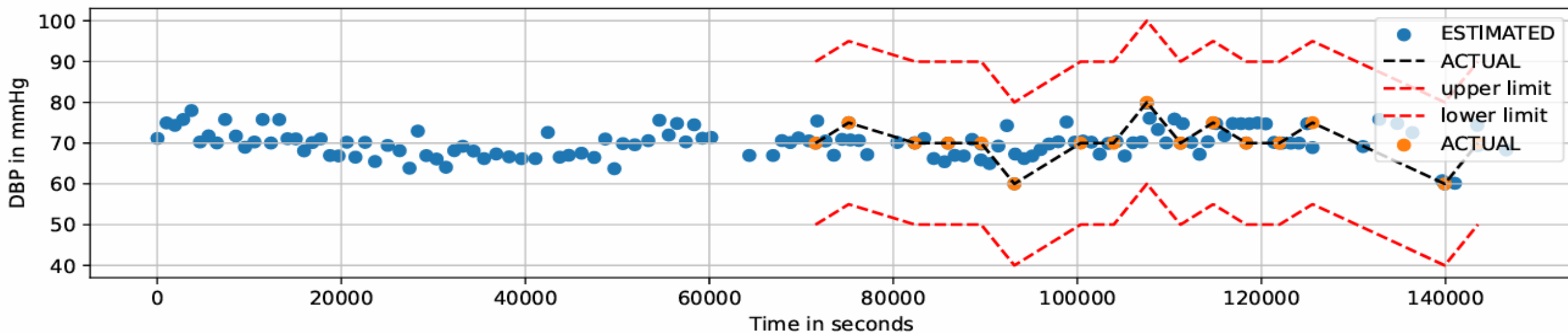
Systolic Blood Pressure (MAE: 0.22) (Min diff: 0.0) (Max diff: 1.49)

Diastolic Blood Pressure (MAE: 0.47) (Min diff: 0.0) (Max diff: 6.11)

Systolic Blood Pressure



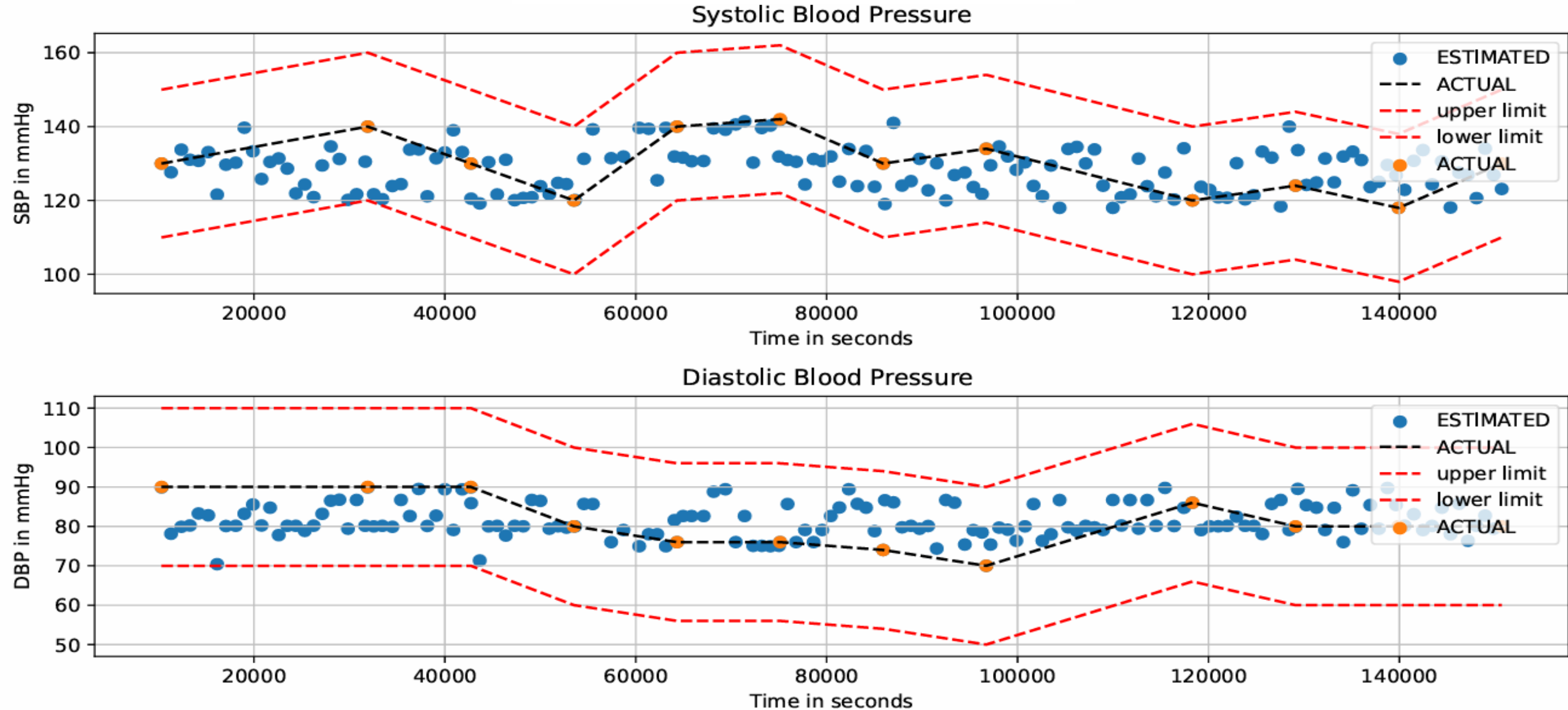
Diastolic Blood Pressure



Person 7 (No. of MSRID's: 12)

Systolic Blood Pressure (MAE: 0.59) (Min diff: 0.0) (Max diff: 6.9)

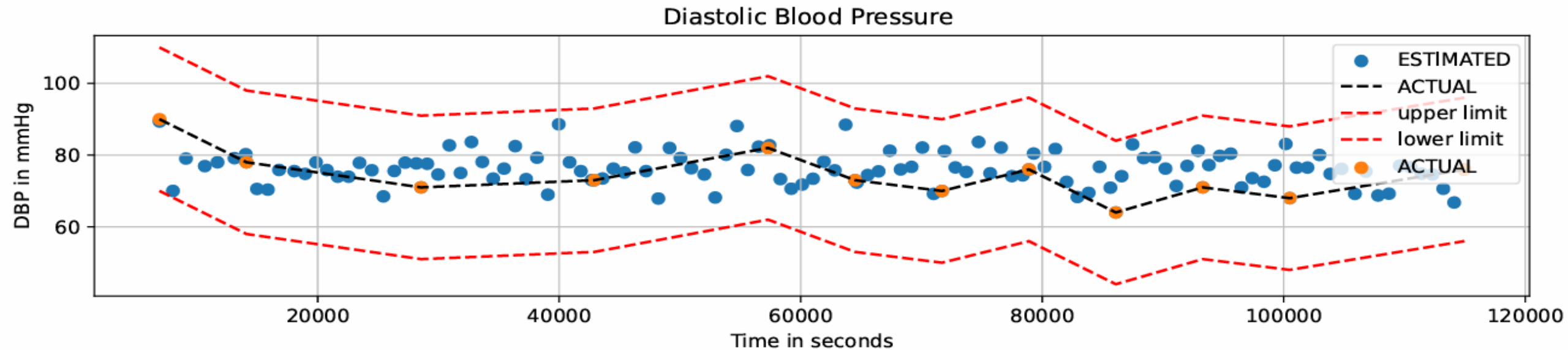
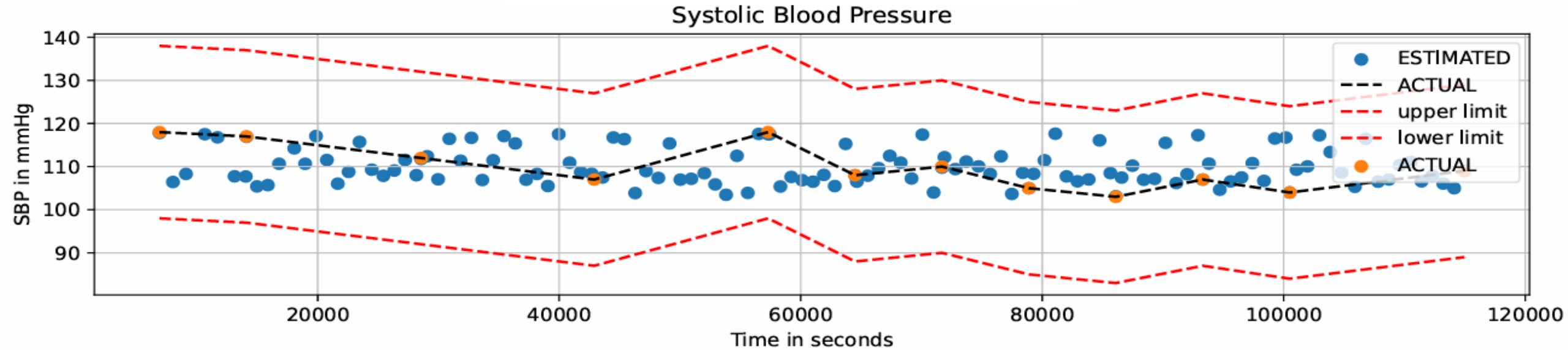
Diastolic Blood Pressure (MAE: 0.04) (Min diff: 0.0) (Max diff: 0.12)



Person 8 (No. of MSRID's: 12)

Systolic Blood Pressure (MAE: 0.14) (Min diff: 0.0) (Max diff: 0.47)

Diastolic Blood Pressure (MAE: 0.05) (Min diff: 0.0) (Max diff: 0.63)



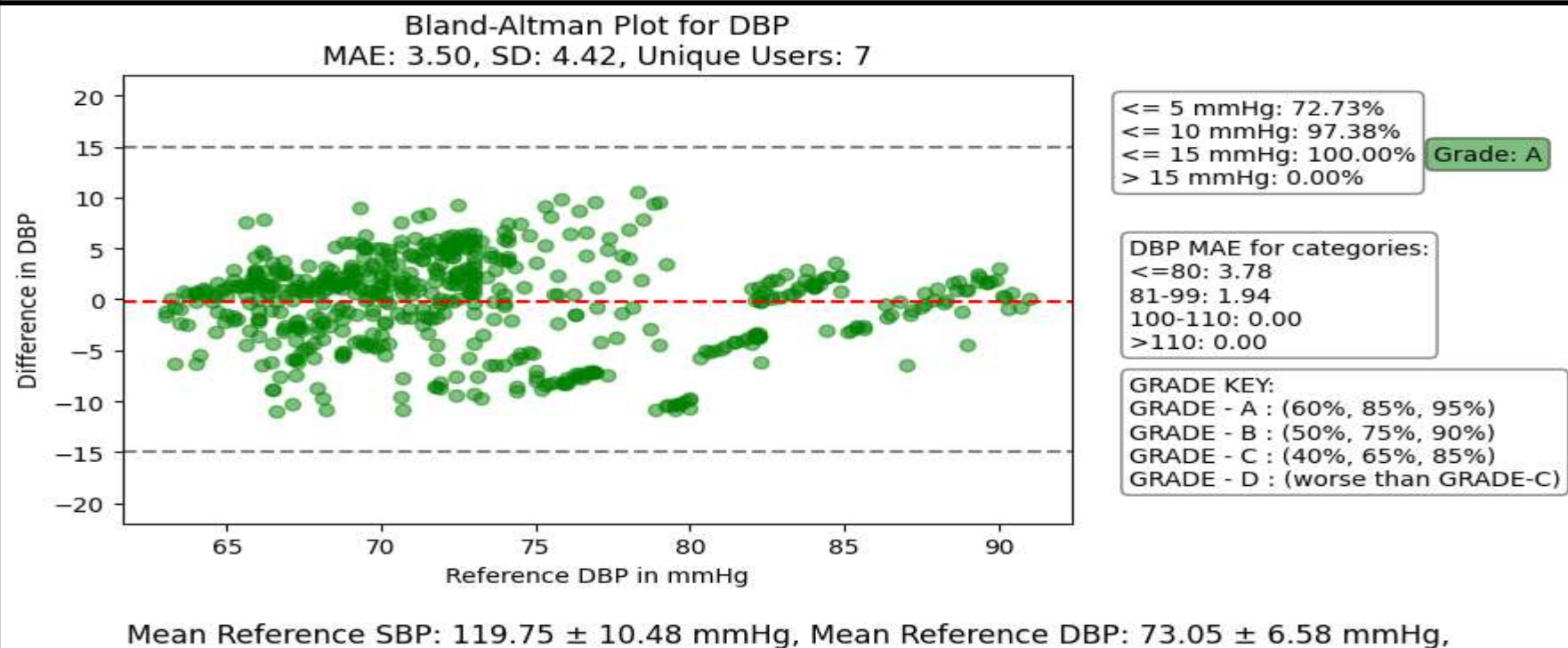
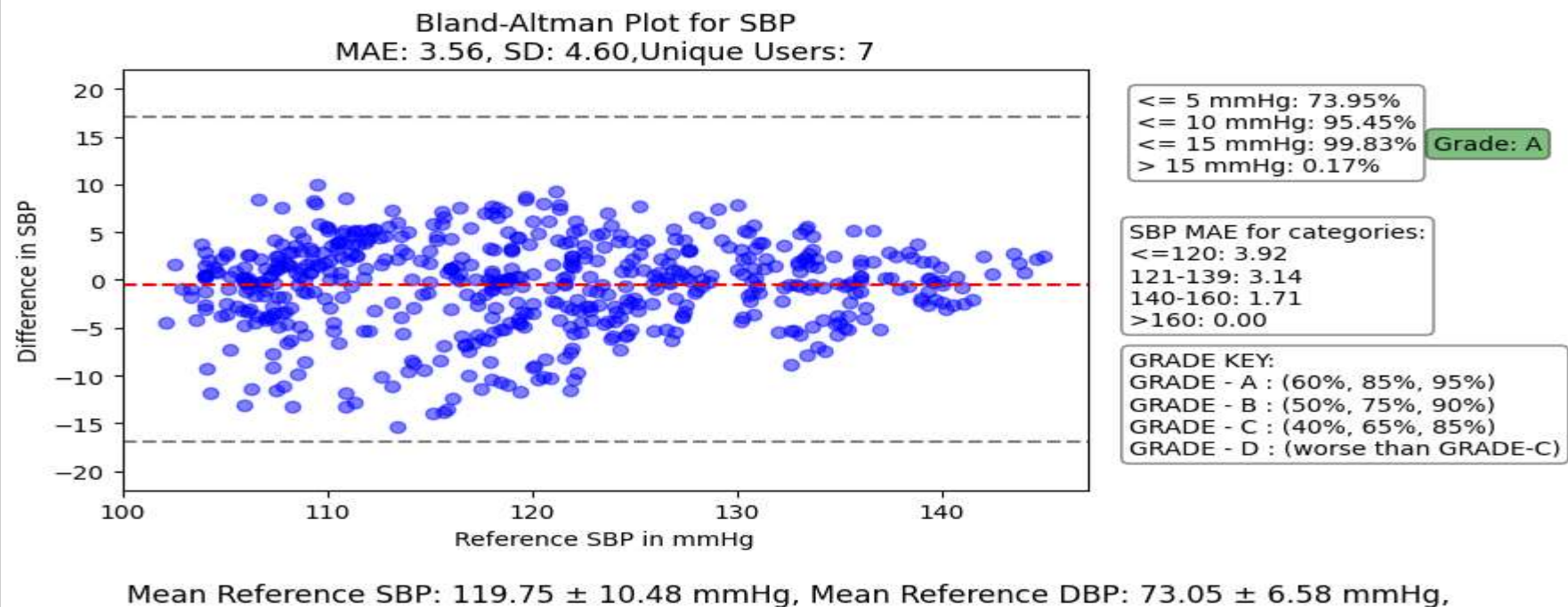
BP Algorithm Finger Data (Generalized) Results- 7 Users

SBP: 90-180, DBP: 60 - 110

Accuracy information:

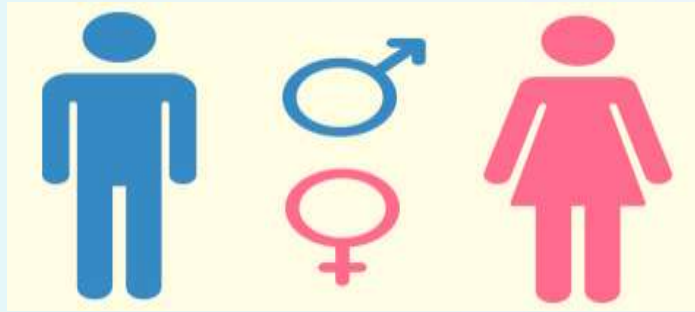
	No. of Measurements	No. of beats	Range in mmHg	Mean Absolute Deviation(MAD in mmHg)	
SBP	550	25000	<120mmHg	3.66960789	3.66374084
			120mmHg - 139mmHg	3.375734532	
			140mmHg - 160mmHg	1.096507289	
DBP	550	25000	<80mmHg	3.54649073	3.500
			80mmHg - 89mmHg	2.954679775	
			90mmHg - 100mmHg	1.694455892	

Bland-Altman plot for finger data

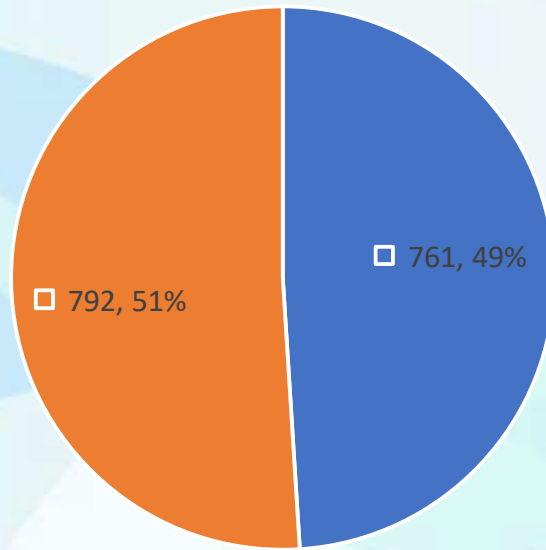


Physiological Data Representation in the Wrist Data

GENDER

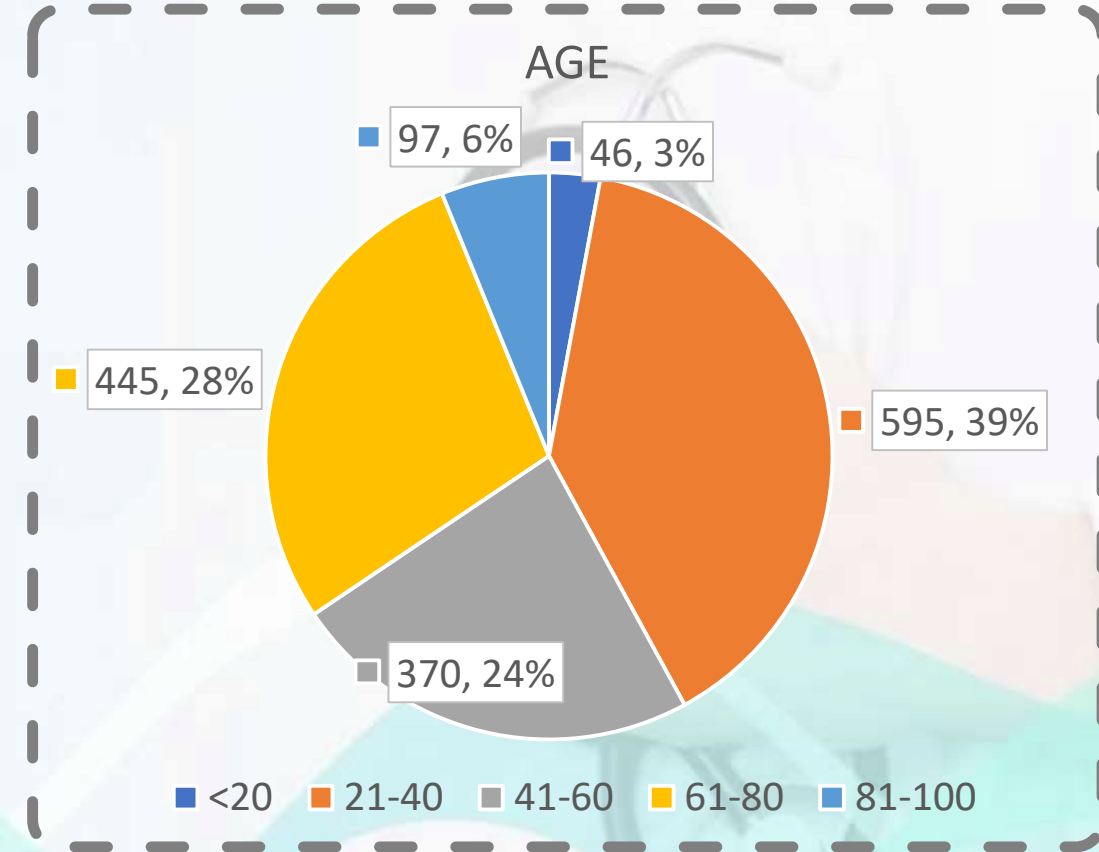


GENDER



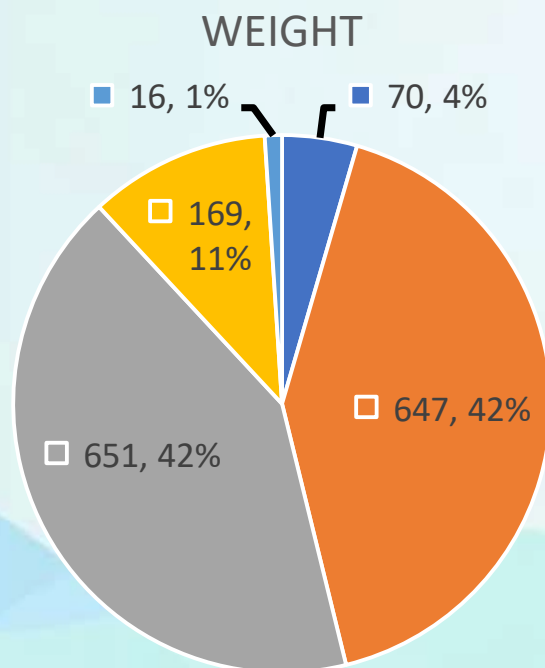
0 - Female 1 - Male

AGE



Physiological Data Representation in the Wrist Data

WEIGHT



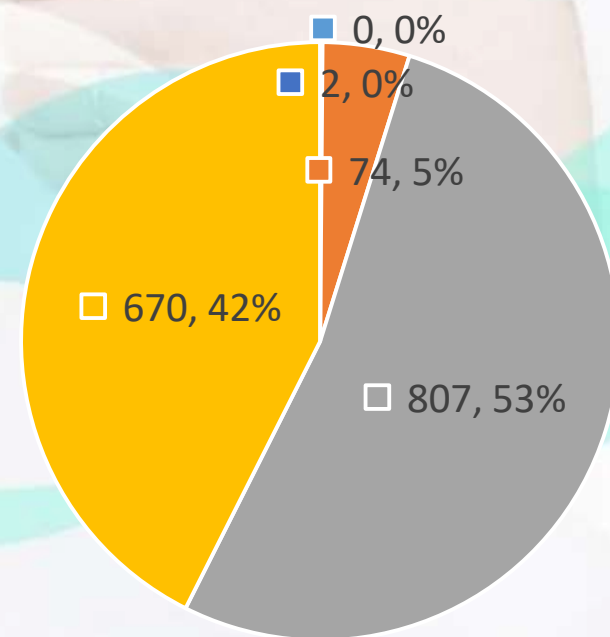
■ <=40 ■ 41-60 ■ 61-80 ■ 81-100 ■ >=101



HEIGHT



HEIGHT



■ <=120 ■ 120-140 ■ 141-160 ■ 161-190 ■ >190

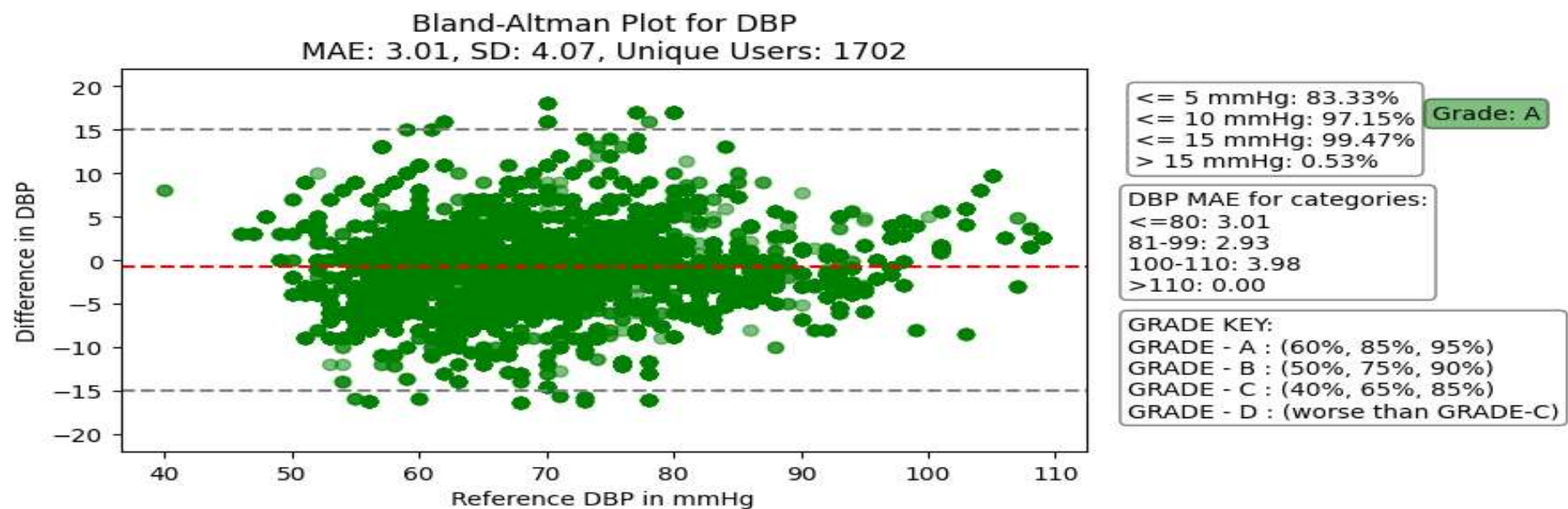
BP Algorithm Wrist Data (Generalized) Results- 1702 Users

SBP: 90-180, DBP: 60 - 110

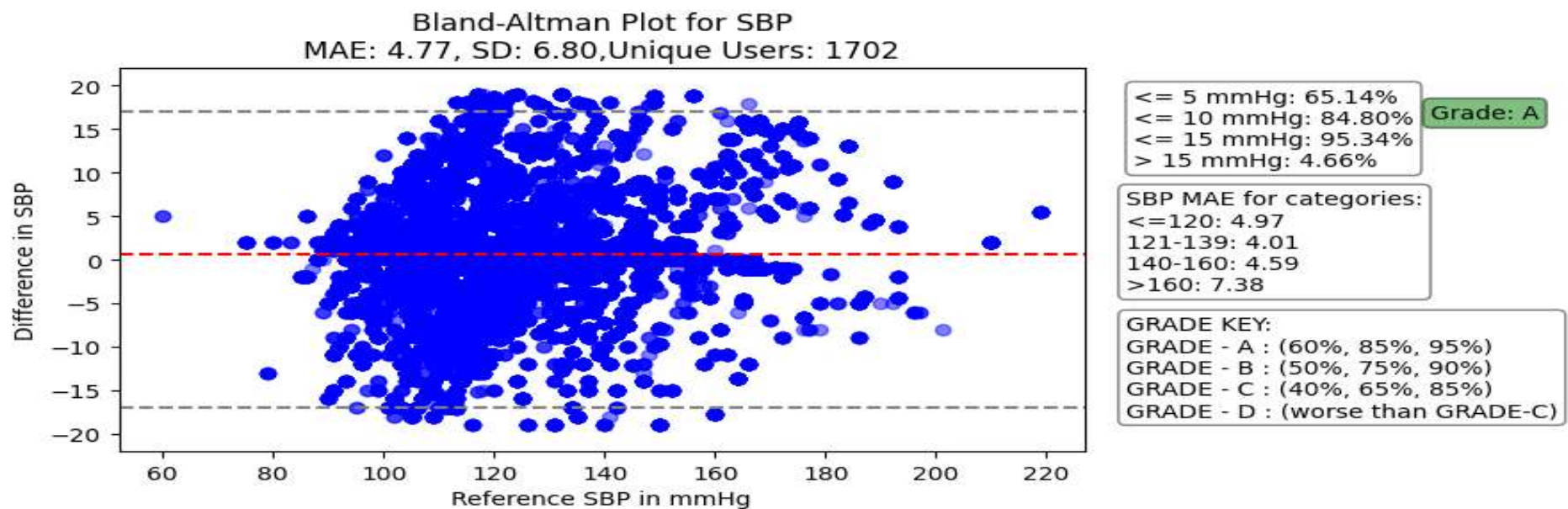
Accuracy information:

	No. of Measurements	No. of beats	Range in mmHg	Mean Absolute Deviation(MAD in mmHg)	
SBP	3000	1,50,000	<120 mmHg	4.999892	4.773743
			120mmHg - 139mmHg	4.041613	
			140mmHg- 160mmHg	4.439756	
			>160mmHg	7.382514	
DBP	3000	1,50,000	<80mmHg	4.729259	3.0007582
			80-89mmHg	4.518468	
			90-100mmHg	6.34477	
			>100mmHg	7.5087	

Bland-Altman plot for wrist data



Mean Age: 52.07 ± 20.87 years, Mean Height: 158.28 ± 10.80 cm, Mean Weight: 64.51 ± 14.80 kg
Mean Reference SBP: 123.49 ± 19.18 mmHg, Mean Reference DBP: 68.85 ± 9.86 mmHg,



Mean Age: 52.07 ± 20.87 years, Mean Height: 158.28 ± 10.80 cm, Mean Weight: 64.51 ± 14.80 kg
Mean Reference SBP: 123.49 ± 19.18 mmHg, Mean Reference DBP: 68.85 ± 9.86 mmHg,

BP Algorithm for Wrist Data from Huawei (Personalized for 2 Users one month every week three readings)

	No. of Measurements	No. of beats	Range in mmHg	Mean Absolute Deviation(MAD in mmHg)	
SBP	11	500	<120mmHg	5.8591	5.8591
			120mmHg - 139mmHg	-	
			140mmHg - 160mmHg	-	
DBP	11	500	<80mmHg	6.50681	4.94075
			80mmHg - 89mmHg	0.780164	
			90mmHg - 100mmHg	-	

Bland-Altman plot for Wrist Data from Huawei (Personalized)

