Addressing the Current Emergency Medical Response System

MAJOR QUALIFYING PROJECT

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by

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1 Abstract

Out of the 25% of preventable mortalities, most happen before ambulances are able to get to the hospital [1]. Currently, pre-hospital care is “an area of limited organizational expertise” [1] and as such is in want of a technology that will take the guess work out of ambulance transportation. We endeavor to design a program that will consider the patient’s needs and the distance of the ambulance from the available hospitals and use this information to choose field hospitals that best meet these requirements. A program is developed that utilizes weighted sums for the importance of the need, combined with whether the given hospital meets that specification. Optimizations are then developed, formulating the Ambulance Problem in terms of binary linear programming.

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2 Related Work

In 2011, a study was performed by Poulymenopoulou, Malamateniou, and Vassilacopoulos on how data could be used by cloud services to automate emergency medical processes [2]. Stemming from an increase in emergency cases requesting ambulance transportation to Emergency Departments, a need was determined for patient and supply information sharing between the Emergency Department and the EMS workers. The responsibility of the technology developed is to take data from patient records, EMS records, and hospital medical records, determine the EMS protocol to take, triage the case, and decide on the most appropriate hospital for the case. The data details the supplies that hospitals provide such as the number of beds available, “available service coverage,” and “the operational status of medical facilities” [2]. The technology comes in the form of both a web and mobile application. In order to assess the trauma level of the patient, the Netherlands Triage System was used, and the emergency medical protocols are the EMS pre-hospital treatment protocols published by the Massachusetts Department of Public Health, Office of Emergency Medical Services. The patient’s case information and the “emergency care ontology” [2] are provided as input to a REST service to assign the urgency level. Once this triaging is done, the hospital selection service (HOS) is ran with input of present and previously established patient data, urgency level, and the emergency care ontology in order to determine which hospital has the best services and resources for the patient. The HOS may also consider load balancing when figuring out which hospital is closest to the patient. The updates on data needed for knowing what beds or tools a hospital has available are maintained by relevant hospital employees. The choice of the hospital is made known to both the EMS and the chosen hospital’s personnel, along with the patient’s case data. So far this study has been limited to applications on a small group of participants because of the risks associated with evaluating performance of the service. How the team implemented load-balancing is not specified either.

Another body of research on hospital selection algorithms is concerned with combining the most effective baseline policies into what the authors call the 3C policy [3]. The Closest policy, which is the first of the four baseline policies, chooses the closest hospital to the patient. The Diversion policy looks at how many beds are available and how many patients are waiting. Then the policy makes a list of the hospitals that do not have any beds and those ones are on diversion. Out of the remaining hospitals the closest one is chosen, or the closest one on diversion if all are on diversion. Next the Join the Shortest Queue (JSQ) policy looks at how many people are waiting at each hospital and chooses the one with the shortest queue of people. Finally, the Shortest Transfer Time (STT) policy focuses on keeping the number of available ambulances up by determining the hospital with the shortest transfer time, or the time for transportation and turnaround time for the ambulance to get going again. The study found that the STT policy was the most effective, with the diversion policy coming in second, the JSQ policy occasionally being a prime candidate, and the closest policy was the worst in many of the cases. The issue with the closest policy is that when hospitals get crowded they are in want of load balancing and ambulances get stuck waiting there. The JSQ policy sends ambulances to less crowded hospitals but this increases the transfer time if that hospital is far away. The diversion policy has the potential to choose a hospital that has long transfer times. The STT policy could be viewed as greedy since it goes for the lowest transfer time and does not pay attention to how this impacts the long-term transfer time. One more surprising finding was that although it was posed that lower transport times would lead to lower response times, some of the results were to the contrary. These four baseline policies were then boiled down to having two factors:

"closeness (minimizing transport time) and congestion (minimizing turnaround time)" [3]. Due to discovering that transport time is not directly correlated to response time, the concept of centrality came into play. If pursuing a lower transport time brings an ambulance away from an area with a high concentration of patients who are waiting, then the next response time is often increased. With this third policy in place, the three policies of Closeness, Congestion, and Centrality can be combined into what is called the 3C policy. The first step in the 3C policy is when an ambulance decides to transfer patient to an ED, identify all hospitals that have an eligible emergency department (ED). Next, estimate the expected transport time to reach each hospital, and acquire the queue length of ED waiting room from each hospital. Then, compute fitness of each hospital based on expected transport time and queue length, which are weighted. Finally, transport patient to the hospital that minimizes fitness. The 3C policy outperformed all of the other policies by being one of the best in 98% of cases and being the absolute best in 26% of cases [3]. Additionally, the 3C policy reduces response time by 99% over the closest policy, 90% over the diversion policy, 68% over the JSQ policy, and 67% over the STT policy [3].

Leo, Lodi, Tubertini, and Di Martino formulated a mixed-integer programming model that decides on an ideal hospital which prioritizes minimizing travel and wait times and using penalties on improper load-balancing of work for the hospitals [4]. The conditions that the solutions must satisfy are: "(a) each request…is assigned to exactly one emergency department…; (b)" the chosen hospital provides fitting medical treatment for the patient's needs; "(c) the expected duration of the trip from [the site of request to the hospital] does not exceed the maximum estimated time for avoiding life-threatening" developments [4]. Constraints are assigned, and it can be noted that the first one ensures that each request must be assigned to a hospital that is capable of providing the needed medical care. The second constraint enforces the time limit of condition (c). The cost is composed of the amount of time that it takes to get from the request location to the hospital and the other part of it is a function of the number of patients awaiting medical care. This second component is where the load-balancing is accounted for by "[estimating] the needed waiting time for processing all…requests assigned to [the hospital] with the aim of penalizing emergency department overload situations" [4]. The waiting functions that the researchers use were created by doing statistical analysis on the datasets from the Department of Epidemiology of the Regional Health Service of Lazio, Italy, which is their ED system. A real-time first aid requests assignment algorithm is proposed as a combination of the MIP model, a relaxation of the MIP model with respect to workload, and "the availability of a quick combinatorial solution of it" [4]. This will serve as a starting point for any continuations of the study and will be an online ambulance request allocation that does triage in a centralized manner.

3 The Ambulance Problem

The purpose of the hospital matching algorithm is to optimize the way that patients are distributed to hospitals based on a variety of factors like distance to the location and what level of care the hospital will need to provide.

The hospital matching algorithm has 3 subcomponents that allow it to perform its operation: the distance calculator, the weighted sum calculator, and the top three field hospitals calculator.

1. There are two distance calculators that are available for use, but currently the algorithm is finding Euclidean distance between the patient location and the hospital locations.
2. The weighted sum calculator takes in the factors that the EMS worker enters and the importance of each for a given hospital and returns the weighted sum.
3. The top 3 field hospitals calculator takes in a list of field hospitals, a list of factors given by the EMS worker, and the importance of each factor and gets the weighted sum for how well each hospital meets the needs. The best three field hospitals are those with the lowest weighted sums, and are returned to the user in order of ranking with the first hospital having the best services for the patient.

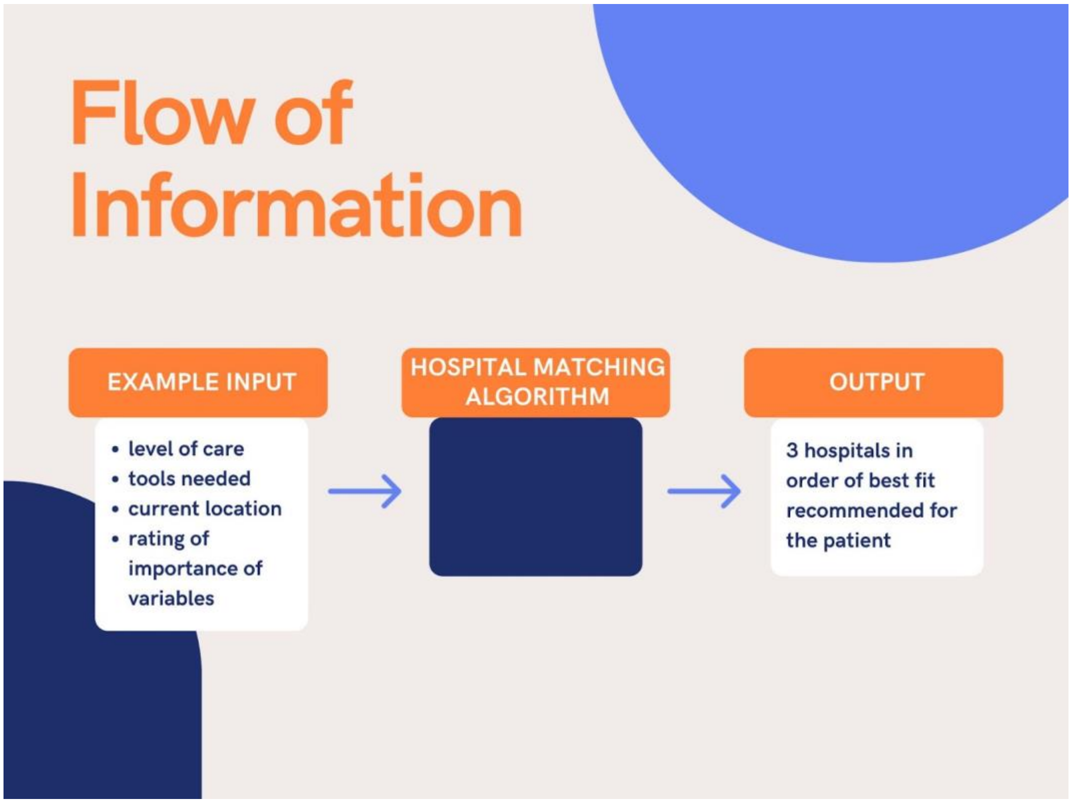

Figure 1: Flow of information for Ambulance program

An EMS worker can be responsible for inputting the patient's preferences information, such as what their state of health or injuries suggest for what level of care or what tools should be available at an ideal hospital. The location of the patient should also be provided in any case. The variables of distance and level of care should also be rated by importance, or provided as 0 if not applicable. The program will then take the variables, their levels of importance, and hospital information related to the variables and calculate three hospitals in order of suitability that it would recommend the patient go to. The way this information is sent through the program is displayed in Figure 1 above.

4 Current State

After getting the program itself to work, I began designing the problem optimization. I started off with modelling the problem in Gurobi with a binary linear programming style. Below is Table 1, which displays the organization of the problem with some sample values.

Hospital	Patient Need #1	Patient Need #2	Distance
1	3	0	20
2	0	5	10
3	3	5	31
4	0	0	11
5	3	5	12

Table 1: Ambulance problem formulation

When you formulate a Linear Program (LP) in Gurobi, there are four components to specifying the problem: decision variables, the objective function, structural constraints, and nonnegativity constraints. The decision variables are what we will control in order to solve our need, in this case we are choosing certain amounts (x_j) of each food type (j). The objective function is the way we calculate what we want to minimize or maximize for the problem, in this case we want to calculate the minimum cost for our choices of amounts of each food. The structural constraints are the requirements that we need to fulfill, in this case the minimum amount of each nutrient (#1 and #2) we need to get from the foods. The nonnegativity constraints are a statement of whether we can have negative amounts of our decision variables, and in our case we cannot so we must have at least 0 units of each food type. If there a hospital does not meet a certain need then that variable will be omitted from the structural constraints. Below in Table 2 are my specifications for the four components to the problem:

Decision Variables	Objective Function	Structural Contraints	Nonnegativity Constraints
$x_j = 0, 1$	minimize	$3x_1+3x_3+3x_5 \geq 3$	Not applicable in case of boolean
$j = 1, 2, \ldots, 5$	$20x_1+10x_2+31x_3+11x_4+12x_5$	$5x_2+5x_3+5x_5 \geq 5$	$j=1, 2, \ldots, 5$

Table 2: Ambulance Linear Program components

Above is the result of running my optimization, with the results behaving as I had expected, and those being a minimum distance of 12 units and hospital 5. After this Gurobi optimization had been squared away, I shifted my focus onto modelling the problem in Gecode, which is a C++ optimizer to match the language the program is written in. I used MiniZinc as an interpreter to write the optimization in, and although the syntax is less readable than Gecode, on the second try I got the proper results, which agreed with those of Gecode. The full write-up for the optimizations I made in Gurobi and Gecode can be found in **Appendix A**.

I also began researching load balancing and different optimization techniques in order to sort the parts of our problem into which ones can be done through optimization and which should be done iteratively. The issue of recommending a hospital based on the distance and the patient's needs is a mixed integer linear programming problem, with the distance being an integer and whether the hospital meets the needs of the patient being a binary value. If we have the potential to distribute our patients across the hospitals more evenly we could use binary linear programming to say whether the patient should go to that hospital and maximize the remaining supplies for a hospital. That is to say that if we know the amounts of supplies for each hospital, then we should favor hospitals that have more supplies available. Now, if the project is able to accommodate the idea of taking multiple patients in an ambulance, I believe that discrete optimization programming would be a potential way to optimize this. Table 3 below displays how this might be organized, as gathered from **Appendix B**.

	Patient 1	**Patient 2**
Time of injury	t_0	$t_0+\epsilon$
Procedure needed	p_0	p_0
Transport time	τ_0	τ_0
Delay permissible	d_0	d_0

Table 3: Discrete Optimization program formulation for multiple patients in ambulance

The budget which the time to transport would have to be constrained to stay below is the delay that is permissible for the patient before their health begins to decline. Finally, triaging would be a binary linear programming problem where it would simply be a matter of assessing which category of trauma center or level of urgency the patient would fall into and saying whether or not the patient falls into each triage level or not.

5 Future Work

The future of my work would be composed of extending the program to have the data of whether the hospital has the supplies to provide for the need the EMS worker specified for the patient and continuing research on load balancing and other optimization techniques. Since the hospital would either have or not have the resources required to meet the patient's need, this would just be a value of 0 or 1. As mentioned previously, this would then be a mixed integer linear programming problem. Then an optimizer like the ones I wrote in Gecode and Gurobi could be used to find the maximum weighted sum value while minimizing the distance between the patient and the hospital.

If we have data on the resources that a hospital has, then we might consider not just what is best for the patient's immediate needs, but also the needs of future patients by load-balancing the patients that we send to hospitals. This would need to consider not just the amount of beds that a hospital has, but the actual capacity that hospitals go by when accepting patients, which tends to be around 85% of the total number of beds [5]. If we were able to do this, my thought would be that the staff would have a better workload, overcrowding would be reduced, and like in a processor, the buffer would be less likely to be blocked. Task-stealing in computing would not be instantaneous in a real-world case like this, so it would be better to think more about the distribution of patients to hospitals beforehand. This might result in longer distances, but according to the delay permissible for the patient, we could do this only for those patients who can afford it and save a reallocation of patients who cannot.

The eCDR for my team's study will be available in WPI's Gordon Library's database and has been submitted for publication [6].

6 References

[1] Mabry, R. & DeLorenzo, R. (2014). Challenges to improving combat casualty survival on the battlefield. *Military Medicine*, *179*(5), 477–482. doi: 10.7205/MILMED-D-13-00417.

[2] Poulymenopoulou, M., Malamateniou, F., & Vassilacopoulos, G. (2011). Emergency Healthcare Process Automation Using Mobile Computing and Cloud Services. *Journal of medical systems*, *36*(5), 3233–3241. doi: 10.1007/s10916-011-9814-y.

[3] Lee, S. (2014). The role of hospital selection in ambulance logistics. *IIE Transactions on Healthcare Systems Engineering*, *4*(2), 105–117. doi: 10.1080/19488300.2014.914608.

[4] Leo, G., Lodi, A., Tubertini, P., & Di Martino, M. (2016). Emergency Department Management in Lazio, Italy. *Omega (Oxford)*, *58*, 128–138. doi: 10.1016/j.omega.2015.05.007.

[5] Gurobi Optimization. (2021, Aug. 3). COVID-19 Hospital Capacity Management using Mathematical Models [Video]. YouTube. **https://www.youtube.com/watch?v=LnxgQmHf-_Q&t=1729s**

[6] Chen, Y., Flanigan, P., Mahoney, E., Miera, A., & Snapperman, B. (2022). Advancing the Current Emergency Medical Response System: A.V.E.M.S.

Appendix A: Ambulance Problem Optimization Writeup

Regarding the diet problem that I did in Gurobi, I followed the video tutorials that can be found here and here for part 2. It is written in Python because that is the most supported language that Gurobi uses, and is good for learning how to use Gurobi since it is readable. The diet problem is basically like if you were to go to the grocery store and want to get the minimum amount of nutrients that you need from a selection of foods while minimizing the cost. Each food has a certain amount of nutrients that it offers, different nutrients, and a cost. When you formulate a Linear Program (LP) for this problem in Gurobi, there are four components to specifying the problem: decision variables, the objective function, structural constraints, and nonnegativity constraints.

Diet Problem Formulation

Food	#1	#2	Cost
1	2	0	20
2	0	1	10
3	3	2	31
4	1	2	11
5	2	1	12

Nutrient requirements:
#1: 21, #2: 12

- Decision Variables
  - x_j = # of ounces of food type $j = 1, 2, \ldots, 5$
- Objective Function
  - minimize $20x_1 + 10x_2 + 31x_3 + 11x_4 + 12x_5$
- Structural Constraints
  - $2x_1 + 0x_2 + 3x_3 + 1x_4 + 2x_5 \geq 21$
  - $0x_1 + 1x_2 + 2x_3 + 2x_4 + 1x_5 \geq 12$
- Nonnegativity constraints
  - $x_j \geq 0, j = 1, 2, \ldots, 5$

The decision variables are what we will control in order to solve our need, in this case we are choosing certain amounts (x_j) of each food type (j). The objective function is the way we calculate what we want to minimize or maximize for the problem, in this case we want to calculate the minimum cost for our choices of amounts of each food. The structural constraints are the requirements that we need to fulfill, in this case the minimum amount of each nutrient (#1 and #2) we need to get from the foods. The nonnegativity constraints are a statement of whether we can have negative amounts of our decision variables, and in our case we cannot so we must have at least 0 units of each food type.

```
gurobi> m = Model()
gurobi> x1 = m.addVar(lb = 0, ub = GRB.INFINITY, obj = 20, vtype = GRB.CONTINUOUS, name = 'food.1')
gurobi> x2 = m.addVar(obj = 10, name = "food.2")
gurobi> x3 = m.addVar(obj = 31, name = "food.3")
gurobi> x4 = m.addVar(obj = 11, name = "food.4")
gurobi> x5 = m.addVar(obj = 12, name = "food.5")
```

Above is where I made the model object (m), and added a variable for each of the foods. By the nonnegativity constraint, the lower bound (lb) must be 0, and the upper bound is not defined so we can set it to infinity. The objective function is about the cost, so for the obj variable we set the cost of each food. The vtype is specified as continuous or integer, which is continuous in our case since our decision variables can be any real number not less than 0. Finally, the name variable is where you can set a name for when you write this out to a file (x_j names are just for the terminal session). We do not need to write out all of these variables for each food, just the variables that change, which are the costs and the food names. After making the variables you must perform ‘m.update()’ to actually write to the model.

```
[gurobi> con1 = m.addConstr(2*x1 + 3*x3 + x4 + 2*x5 >= 21, "nutrient.1")
[gurobi> con2 = m.addConstr(x2 + 2*x3 + 2*x4 + x5 >= 12, "nutrient.2")
[gurobi> m.optimize()
```

Next, we can make the structural constraints and add them to our model. You will use x_j names for your food variables here and multiply them by their amounts of nutrients. For foods that do not have a certain nutrient, you do not have to write ‘0*x_j’, just omit. I went straight into optimizing the problem because the model will be updated automatically with the optimize function.

```
gurobi> m.optimize()
Gurobi Optimizer version 9.1.2 build v9.1.2rc0 (mac64)
Thread count: 2 physical cores, 4 logical processors, using up to 4 threads
Optimize a model with 2 rows, 5 columns and 8 nonzeros
Model fingerprint: 0x7d44349f
Coefficient statistics:
  Matrix range     [1e+00, 3e+00]
  Objective range  [1e+01, 3e+01]
  Bounds range     [0e+00, 0e+00]
  RHS range        [1e+01, 2e+01]
Presolve removed 0 rows and 3 columns
Presolve time: 0.00s
Presolved: 2 rows, 2 columns, 4 nonzeros

Iteration    Objective       Primal Inf.    Dual Inf.      Time
       0    0.0000000e+00   1.650000e+01   0.000000e+00      0s
       2    1.3100000e+02   0.000000e+00   0.000000e+00      0s

Solved in 2 iterations and 0.00 seconds
Optimal objective  1.310000000e+02
gurobi> x1.X
0.0
gurobi> x2.X
0.0
gurobi> x3.X
0.0
gurobi> x4.X
1.0
gurobi> x5.X
10.0
gurobi> x4.X + 2*x5.X
21.0
gurobi> 2*x4.X + x5.X
12.0
```

Here is the solution of the problem, with the minimum cost being $131 and the foods that were chosen were 1 unit of food 4 and 10 units of food 5.

The Ambulance Problem in Gurobi

Firstly, what is the problem I want to model?

Well, there is a patient who needs to get to a hospital, preferably the one that suits their needs the best. A patient has needs, or constraints, which the hospital must satisfy. If the EMT/EMS operating the app determines that the patient needs a certain level of care, the recommended hospital should meet this demand, especially if the EMT/EMS ranks this demand as having high importance.

Following suit as I did for the diet problem, we can represent the Ambulance Problem as such:

The Ambulance Problem Formulation

Field Hospital (FH)	#1*	#2*	Distance
1	3	0	20
2	0	5	10
3	3	5	31
4	0	0	11
5	3	5	12

*ranking num if meets demand, 0 if not

Demand Requirements:

#1 ultrasound machine (ranked 3) #2: level 4 trauma center (ranked 5)

Decision Variables:

x_j = to go to FH or not

j = 1, 2,…, 5 *for each FH option

Objective Function:

minimize

$20x_1 \parallel 10x_2 \parallel 31x_3 \parallel 11x_4 \parallel 12x_5$

Structural Constraints:

$3x_1 + 0x_2 + 3x_3 + 0x_4 + 3x_5 >= 3$ *should offer at least one FH that meets requirement

$0x_1 + 5x_2 + 5x_3 + 0x_4 + 5x_5 >= 5$

Nonnegativity Constraints:

$x_j = 0,1$

j = 1, 2,..., 5

The decision variables are what we will control in order to solve our need, in this case we are choosing whether or not to go to (x_j) each field hospital option (j). The objective function is the way we calculate what we want to minimize or maximize for the problem, in this case we want to calculate the minimum distance from patient to FH for our choices of which field hospitals to recommend. The structural constraints are the requirements that we need to fulfill, in this case the minimum ranking we need to achieve to say we satisfied each demand (#1 and #2) the patient makes of the FH. The nonnegativity constraints are a statement of whether we can have our decision variables being boolean values, and in our case we cannot only half satisfy a demand, it either is or it is not.

```
gurobi> m = Model()
gurobi> x1 = m.addVar(lb = 0, ub = 1, obj = 20, vtype = GRB.BINARY, name = 'fh.1')
gurobi> x2 = m.addVar(lb = 0, ub = 1, obj = 10, vtype = GRB.BINARY, name = 'fh.2')
gurobi> x3 = m.addVar(lb = 0, ub = 1, obj = 31, vtype = GRB.BINARY, name = 'fh.3')
gurobi> x4 = m.addVar(lb = 0, ub = 1, obj = 31, vtype = GRB.BINARY, name = 'fh.4')
gurobi> m.remove(x4)
gurobi> x4 = m.addVar(lb = 0, ub = 1, obj = 11, vtype = GRB.BINARY, name = 'fh.4')
gurobi> x5 = m.addVar(lb = 0, ub = 1, obj = 12, vtype = GRB.BINARY, name = 'fh.5')
gurobi> m.update()
```

Above is where I made the model object (m), and added a variable for each of the FH's. By the nonnegativity constraint, the lower bound (lb) must be 0, and the upper bound is 1 since we either go to an FH or we do not. The objective function is about the cost, so for the obj variable we set the distance to each FH, as this could impact the state of the patient by the time they arrive. The vtype is specified as binary in our case since our decision variables can either be 0 or 1. Finally, the name variable is where you can set a name for when you write this out to a file (x_j names are just for the terminal session). We need to write out all of these variables for each FH, because the variables we use are not the defaults. After making the variables you must perform 'm.update()' to actually write to the model. If you mess up on adding a variable like I did with x_4, you can use the Model.remove(var) method to remove it.

```
gurobi> con1 = m.addConstr(3*x1 + 3*x3 + 3*x5 >= 3, "demand.1")
gurobi> con2 = m.addConstr(5*x2 + 5*x3 + 5*x5 >= 5, "demand.2")
gurobi> m.optimize()
```

Next, we can make the structural constraints and add them to our model. You will use x_j names for your FH variables here and multiply them by the rankings of the demands the FH's meet. For FH's that do not meet a certain demand, you do not have to write '$0*x_j$', just omit. I went straight into optimizing the problem because the model will be updated automatically with the optimize function.

```
gurobi> m.optimize()
[Gurobi Optimizer version 9.1.2 build v9.1.2rc0 (mac64)
Thread count: 2 physical cores, 4 logical processors, using up to 4 threads
Optimize a model with 2 rows, 5 columns and 6 nonzeros
[Model fingerprint: 0x8c7328dc
[Variable types: 0 continuous, 5 integer (5 binary)
[Coefficient statistics:
  Matrix range     [3e+00, 5e+00]
  Objective range  [1e+01, 3e+01]
  Bounds range     [1e+00, 1e+00]
  RHS range        [3e+00, 5e+00]
Found heuristic solution: objective 12.0000000
Presolve removed 2 rows and 5 columns
Presolve time: 0.00s
Presolve: All rows and columns removed

Explored 0 nodes (0 simplex iterations) in 0.01 seconds
Thread count was 1 (of 4 available processors)

Solution count 1: 12

Optimal solution found (tolerance 1.00e-04)
Best objective 1.200000000000e+01, best bound 1.200000000000e+01, gap 0.0000%
gurobi> x1.X
0.0
gurobi> x2.X
0.0
gurobi> x3.X
0.0
[gurobi> x4.X
0.0
[gurobi> x5.X
1.0
```

Here is the solution of the problem, with the minimum distance being 12 and the FH that was chosen was FH 5.

The Ambulance Problem in Gecode

```
var bool: FH1;
var bool: FH2;
var bool: FH3;
var bool: FH4;
var bool: FH5;

constraint 3*FH1 + 3*FH2 + 3*FH5 >= 3;
constraint 5*FH2 + 5*FH3 + 5*FH5 >= 5;

solve minimize 20*FH1 + 10*FH2 + 31*FH3 + 11*FH4 + 12*FH5;
```

Here I have modeled the Ambulance Problem with the MiniZinc IDE. My variables are booleans, which removes the need for a constraint of 0 or 1 for each of the field hospitals. I tell the program to minimize the distance for the field hospital it chooses, as seen in the final line. However, I have gotten unexpected results from this model, so I will need to alter this model to get the same results as I did with Gurobi.

For documentation's sake, below is a screenshot of my results. By looking at both the rankings and the distance for these chosen field hospitals, it does not seem to be minimizing distance or maximizing rankings.

```
Running fh.mzn
FH1 = true;
FH2 = false;
FH3 = true;
FH4 = false;
FH5 = false;
----------
FH1 = false;
FH2 = true;
FH3 = false;
FH4 = false;
FH5 = false;
----------
==========
Finished in 72msec
```

Here, depicted below is the new version of the Gecode code made with MiniZinc that provides the two best solutions to the problem. This resolves the issue of the last code that was providing answers that did not match the choices I expected.

fh.mzn

```
int: n;
int: p = 2;
array[1..n] of var bool: x;
array[1..n] of var int: distance;

array[1..p] of int: limits;
array[1..n] of int: ultrasoundmachine;
array[1..n] of int: level4traumacenter;

var int: cost = sum(i in 1..n) (distance[i]*x[i]);

solve minimize cost;

constraint
        sum(i in 1..n) (x[i]*ultrasoundmachine[i]) >= limits[1]
        /\ sum(i in 1..n) (x[i]*level4traumacenter[i]) >= limits[2]
;

% data
n = 5; %num of field hospitals
distance  = [20, 10, 31, 11, 12]; %distance to each field hospital
limits = [3, 5]; % requirements for each demand

ultrasoundmachine = [3, 0, 3, 0, 3];
level4traumacenter = [0, 5, 5, 0, 5];

output
[
  "cost: " ++ show(cost) ++ "\n" ++
  "x: " ++ show(x) ++ "\n"
];
```

Output

```
Running untitled_model.mzn
cost: 30
x: [true, true, false, false, false]
----------
cost: 12
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Appendix B: The White Paper Draft

Title:

Name of org. submitting:

WPI Names of any participating orgs: none

CAGE code:

Name, addr, email, phone POC: 1

1 Technical Content

1.1 Executive Summary

There is substantial overlap between the scheduling and dispatching of medi cal resources (e.g., transport, field hospitals, personnel, supplies) in multi- and mass-casualty situations and the scheduling and dispatching of computational tasks onto computer resources. Scheduling and dispatching based upon time utility functions[149] is already used by the military, but not, to our knowledge, in pre-hospital care. While this technology has already shown its usefulness in other domains, applying this technology to triage is innovative. The proposed applied research is to transfer this advanced technology to, and demonstrate its use for, pre-hospital medical care in a prototype. In a triage situation, medi cal care is rationed and patient outcomes are achieved. In deploying computer resources for efficiently generating value with multiple resources from among a multiplicity of tasks, these ideas occur as amount of resources applied and amount of utility obtained. Migrating to a rationing methodology where pa tient care is scheduled and dispatched according to principle of "most utility expected to be obtained" could be disruptive to the scenario of provision of care. Yet this technique is expected to deliver more value in terms of patient outcomes while using the same resources. The intended result is to improve Army operational capability in the domain of human performance of medical care personnel. This work aims to provide "effective augmentation of Soldiers in areas of cognition, perception, and physical performance", for medical person nel. Those Soldiers involved in choosing the particular application of medical resources (including personnel) that can be expected to yield the most value in terms of patient outcome, can be aided by decision support. The decision sup port system proposed herein will be informed by individual patient vitals signs, and also by machine learning training over databases of related information.

Medical personnel in field hospitals save up to 98% of patients who arrive alive (Mabry 2015). The keyword is alive. Approximately 87.3% (n = 4,596) of injury related deaths occur before the patient arrives at a field hospital and, of those deaths, up to 25% (n = 3,040) are preventable (Eastridge 2012). For improvement, we look to support pre-hospital care. In a mass-casualty situation, pre-hospital care, including transport, is subject to relative scarcity. In such situations, triage is applied. Within the categories created during triage, further optimization is sought. Inspired by a proven technology from the scheduling and dispatching of computational tasks to computer resources, we aim to schedule and dispatch medical resources over a collection of patients, in order to deliver a larger percentage of casualties, yet living, in time for field hospitals to provide care. AVEMS uses a patient's vital signs collected from sensors, including the time course of vital signs, to estimate the time available for transport, such that the time for the field hospital's medical procedures, corresponding to the estimate of the injuries, will be available while that patient is alive. Thus a patient whose care is more urgent can precede a patient whose care is less urgent. A patient who is closer to a field hospital might wait longer for transport than a patient who is farther away, but more in need of transport from a standpoint of urgency.

With sensor data from wearable sensors, and communications technology, we can pool data from casualties. This data can inform caregivers performing triage in multi- and mass-casualty situations. An indicator associated with this electronics can be used to signal to the emergency medical personnel which patient has been chosen by the medical care team to be next for treatment.

By working with this data, applying some algorithms from dynamic schedul ing and dispatching of computational tasks onto computer resources, attempting to quantify the amount of patient well-being that is obtained through the ap plication of medical resources, we intend to provide a decision-support tool's initial recommendations for assigning, in the pre-hospital time-frame, patients to transportation resources (which may carry resources such as blood to the patient), and destination field hospitals.

We also intend to program the decision support tool so that it will recalculate its recommendations in response to editing of the plan by the users.

1.2 Discussion

1.2.1 Scientific Research Objective

The objective is to save more lives, and improve medical outcomes for casualties in scenarios where triage is performed. The medical resources available (numbers and locations of beds, field hospitals, personnel, supplies, etc.) are the same before and after the sought improvement.

By definition, relative to the medical needs, there is a scarcity of care, and thus assignment of patient care tasks to patient care resources must be done. The improvement is obtained by a different scheduling and dispatching of care to the patient population. This assignment must be done in a dynamic and complicated environment; personnel carrying out this assignment can be aided by decision support. The decision support provides an intial recommendation, and the personnel can override a recommendation, and see a revised recommen dation.

Our aim is that the care is deployed to the greatest effect, in terms of the most restoring of Soldier welfare.

1.2.2 Approach

The approach makes use of data from wearable sensors for the specific patient. There are also a small number of indicator LEDs on this equipment pack. It is true of the present system of triage that patient data is provided, and choices about the sequencing of patients for care are made. At this level of detail our approach is the same. It is the method by which the choices about sequencing of patients for are made that may differ. An example exhibits the difference. The principle is described next.

An example scenario demonstrates the difference that principles for choosing the next patient can make.
In this example there are two patients, and one medical resource. A timeline is shown in Figure 1. Scenario, first method of triage

The first patient is injured at time t_0. Medical staff decide that this patient should receive procedure p_0, which implies transport. The expected time for transport plus treatment is τ_0. (Transport includes dispatching a vehicle to the site of injury, bringing the Soldier to the hospital and transferring to hospital care.) It is the case that this patient can be expected to survive with the same outcome if treatment were to be delayed by d_0. The delay d_0 is greater than the time to transport and administer the treatment, τ_0. Transport to hospital commences. The second patient is injured at time $t_0 +$, where is chosen to be long enough for the treatment of the first patient to have commenced. Medical staff decide that this patient should receive procedure p_0. Unlike the first patient, this patient cannot be expected to survive with the same outcome, if treatment were to be delayed. When the treatment sequence treats the first patient first, the second patient's outcome is not as good as it might have been. Additional transport commences.

Scenario, second method of triage

The first patient is injured at time t_0. Medical staff decide that this patient should receive procedure p_0, which implies transport. The expected time for transport plus treatment is τ_0. (Transport includes dispatching a vehicle to the site of injury, bringing the Soldier to the hospital and transferring to hospital care.) It is the case that this patient can be expected to survive with the same outcome if treatment were to be delayed by d_0. The delay d_0 is greater than the time to transport and administer the treatment, τ_0. Transport to hospital commences. The second patient is injured at time $t_0 +$, where is chosen to be long enough for the treatment of the first patient to have commenced. Med ical staff decide that this patient should receive procedure p_0. Unlike the first patient, this patient cannot be expected to survive with the same outcome, if treatment were to be delayed. Either additional transport commences if avail able, or the first transport is redirected to the second patient, based upon the following considerations: Redirection results in a reduction of transport time for the second patient that can be expected to be significant in terms of outcome for second patient.

Redirection results in an increase of transport time for the first patient that can be expected to be insignificant in terms of outcome for the first patient.

As Figures 1 and 2 show, there can be situations where more lives are saved, or more patient welfare is saved, when one patient may be safely delayed so that another may be safely expedited. Thus the ability to perform the scheduling and dispatching with knowledge of which patients require to be expedited and which patients may safely wait is needed. When the ability to make these diagnoses is extended by data transmission, and supported by a fuller dataset (not only instantaneous vitals but also their history), the opportunity to save Soldier welfare is increased.

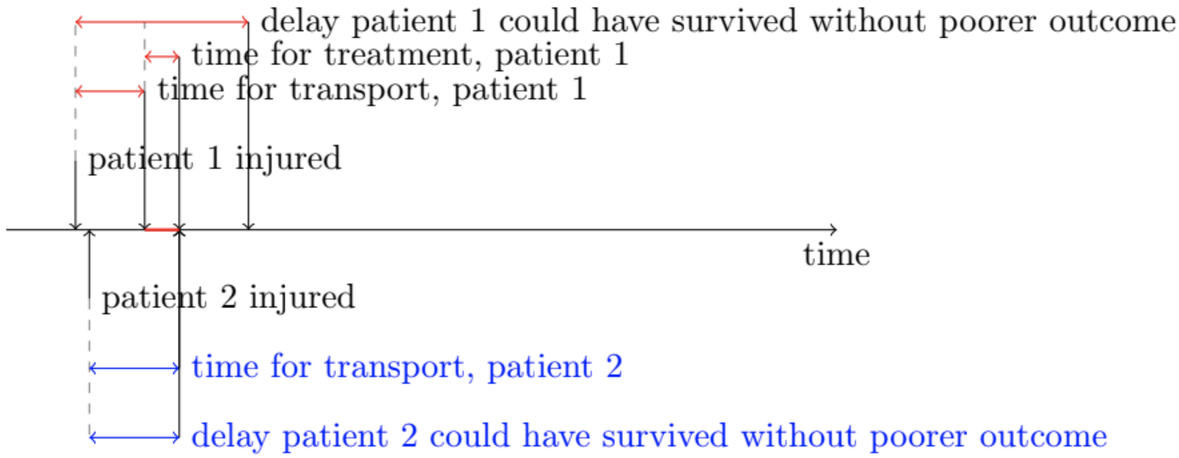

Figure 1: Timelines for approach one.

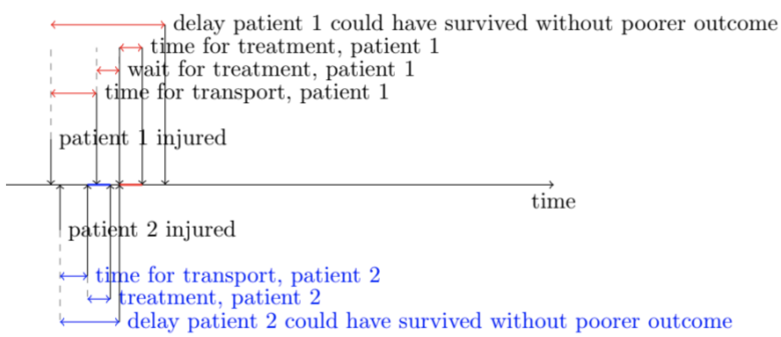

Figure 2: Timelines for approach two.

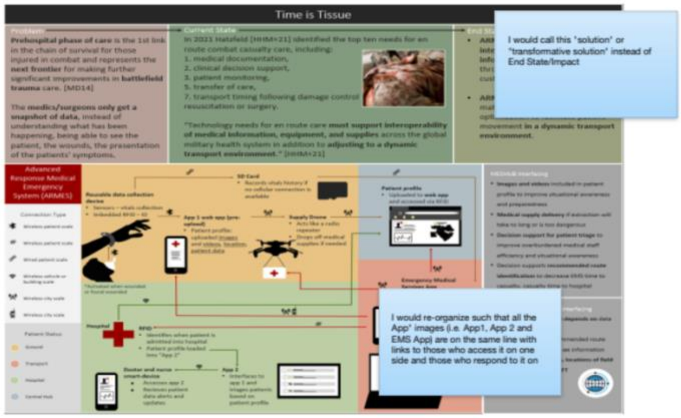

Figure 3: Sensor data from the patient is used in preparing, within a mo bile phone geographical information system (GIS) software, the 9-line form, for transmission into the Blue Forces application.

Figure 4: Sensor data is input to the convex function parameter estimation process. This process is to be trained on vital signs and other data, and labeled with associated medical treatment, especially the length of time to stabilize the patient.

Moreover, situational awareness is increased, because people supplying trans port will receive information about whether or not patients in their care are next in sequence, and also because more data from patients can be delivered to hos pitals. We aim to provide a force multiplier by transmitting the judgement of the medical personnel, such that those personnel, with the support of the sys tem, control the indicator LEDs allowing less skilled personnel to identify the patient next in sequence for care. One force multiplier arises because those pa tients who seem able to sustain a delay can be differentiated from those patients who cannot, and the attending personnel can devote their attention in the most effective way.

The approach also uses a collection of historical data from many casualties.

@Alex: Consider placing the one-pager here, and then consider describing the places that the data reside, and where the computations are carried out.

There is an artificial intelligence (AI) component that uses the data from the individual patient to predict certain parameters (see below). The ability to predict results from training on the collection of data from many casualties.

The parameters whose values are estimated by AI are then used to represent the situation as a time/utility function.

The time/utility function for each patient in a multi-casualty situation is input to the scheduling and dispatching computation, along with that of all the other casualties in a geographic area served by a (dynamic) set of field hospitals (and transport vehicles and other resources).

The result is a (continually updating) recommendation for scheduling and

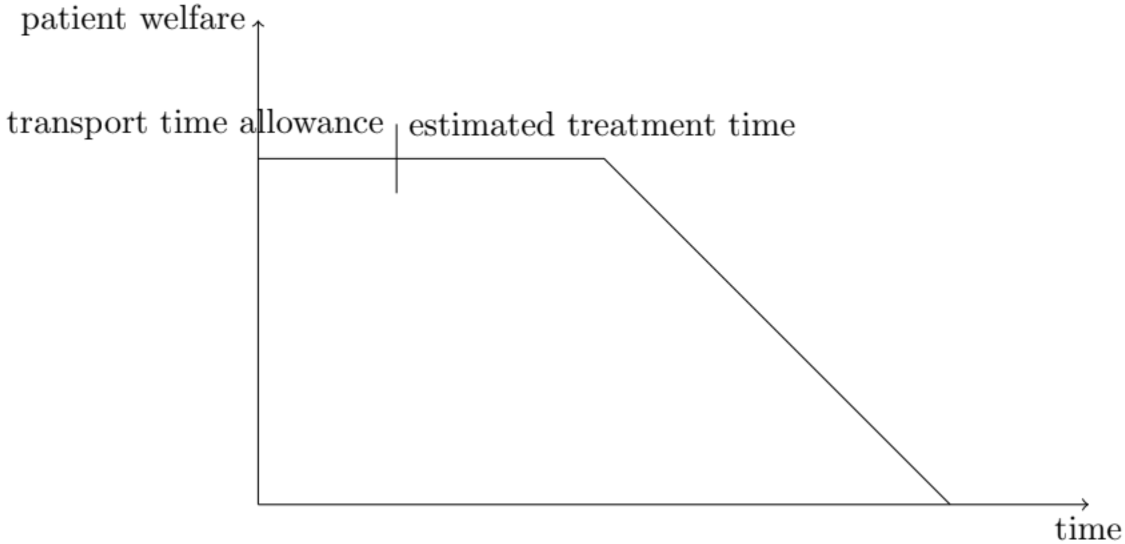

Figure 5: A simple convex function with three parameters: initial height, time at height, angle of descent. The time at height will be divided into two parts: al lowed transport time, estimated time needed for treatment at hospital. Allowed transport time = time at height - estimated time needed for treatment.

dispatching medical resources to each individual patient. This is a decision support system for triage.

Time/Utility Function The convex curve described above is an example of a time/utility function. The vertical axis shows the value, in our case, patient welfare. The horizontal axis is time. An interval of time devoted to restor ing patient welfare can successfully aid the patient, if the interval begins soon enough. If the interval begins too late, the patient is lost, or the amount of patient welfare that can be restored is diminished.

With sensor data from wearable sensors, and communications technology, we can pool data from casualties. This data can inform caregivers performing triage in multi- and mass-casualty situations.

By working with this data, applying some algorithms from dynamic schedul ing and dispatching of computational tasks onto computer resources, attempting to quantify the amount of patient well-being that is obtained through the ap plication of medical resources, we intend to provide a decision-support tool's initial recommendations for assigning, in the pre-hospital time-frame, patients to transportation resources (which may carry resources such as blood to the patient), and destination field hospitals.

We also intend to program the decision support tool so that it will recalculate its recommendations in response to editing of the plan by the users.

Obtaining the Convex Value vs. Time Characterization One use of the sensor data (including its time course for the patient) is to obtain three quantities.

Figure 6: Notional presentation to... Are there multiple different?

For finding out how long it might take to treat a patient, from the vitals, we divide the problem. Part 1: get from vitals to treatment protocol, Part 2: get from treatment protocol to time. The estimates may inbdeed have variances that are large.

(Hi team, Concerning the notion of estimated time needed for treatment, this is not supposed to include long-term recovery, this is intended to mean the care needed to bring the patient to a state from which longer term care may commence. I'm thinking "while in the emergency room". I'm vague about this. Someone who knows this environment better will, I hope, clean up the language. Maybe there is the idea of the immediate critical care team, and the idea of a handoff to a different team.)

Looking at this figure we can see what the algorithm is dealing with. The time at which the decline in the ability to restore the patient occurs is made equal to the time by which the patient's initial treatment needs to be completed. This might be quite significant. Compare this with an emergency operation that concludes with a patient going into long term recovery. There might not be a lot of attention paid to by how much *time* that patient escaped a worse outcome. By noticing that time interval, and adjusting it to be small, we might be using a resource that people are not paying a lot of attention to. The benefit is, that time becomes available for the "transport time allowance". The risk is, we estimate the treatment time to be smaller than it actually is, and lose the patient's welfare. So we need to be somewhat conservative in our estimate of treatment time. Moreover, we can expect that medical personnel performing this treatment might be subject to more stress than before.

The values for initial height, time at height and angle of descent could be estimated by using machine learning. We could use annotated patient data to train machine learning algorithms to classify patient data, such that the trained device would estimate these three values from newly input patient data.

Human-Computer Interfaces for Medical Personnel The several human computer interfaces provide functionality...

1.2.3 Relation to similar research

Obtaining vital signs and related health metrics Hi team, There are lots of publications in this area.

Mobile phone supported open source GIS for describing location and launching 9-line form Hi Brandon, thinking of you here.

Local storage

Transmission

Presentation to Health Professionals Hi Alex, you've been thinking about this for years

Carrying out Triage

Carrying out Triage based upon Situational Awareness

Carrying out Triage based upon vital signs

Utility-based Dynamic Scheduling/Dispatch Hi Patrick, you've been reading Jensen's work Hi Yang Chen, you've been thinking about AI and ML and training an algorithm to predict time-remaining-for-treatment, and descent rate for ability to save patient

Optimization Applied to Transporting Patients I began optimizing the problem of recommending field hospitals according to patients' demands using the Python-based modeling software, Gurobi. I modeled it as such: the decision variables for the problem are the field hospitals which the program has to choose between, the objective is to minimize the distance that it takes to reach the field hospital based on the patient's location, and the structural constraints account for the rating of importance that the EMS worker designates for the patient's needs. The values for the field hospital variables can either be 0 or 1 since the patient should either be recommended to go to a given hospital or they should not. Modelling this in Gurobi has provided the solution that I expected, and so I have moved on to modeling the problem in Gecode using the MiniZinc IDE, since this is based on C++ which fits with the rest of our codebase for this problem. I have replicated my model in MiniZinc, however Gecode is not giving the answer I would expect based on the results in Gurobi, so I will continue to work to right this.

Decision Support for Health Professionals Scheduling and dispatching of tasks characterized by time/utility functions has been applied, perhaps mainly in classified military systems.

Across the world there are multiple standards for how triage is performed. That dissertation from spring 2021 about whether or not a MEDEVAC is dispatched.

How is the next patient to be treated determined?

(Hi Alex, When your dad is feeling better, perhaps you can ask him how we can get the benefit, in terms of convincing program managers about this technology, of military experience that we do not share. One part is, Doug Jensen has said he would work on this with us, and he's one who has been doing the work we don't know much about.)

1.2.4 Facilities and Infrastructure

PI's Current Computing Facilities and Resources

WPI's High Performance Research Cluster

WPI runs a high performance research cluster with 20 high end servers and 48- GPU cluster. This cluster was specifically created to support big data research such as the one described in this proposal. This cluster is managed using cutting edge virtualization technology and has an impressive collection of data analytics and machine learning software including MATLAB, Weka and Nvidia GPGPU computing compile IDE.

WPI Computer Science Departmental Computer Facilities

The WPI CS department has eight labs dedicated to CS education and re search. The department's compute servers consist of 4 Opteron nodes with 24 processors and 56GB RAM total. Four dual Xeon servers with 12 GBRAM, several Pentium 4 servers, and one UltraSparc are dedicated to different re search groups. Additionally, one 1.2Ghz AMD Athlon XP with 1GB RAM is available for compatibility testing. All departmental machines use SuSE Linux or FreeBSD as their operating system, but FreeBSD, Solaris, and several other versions of GNU/Linux are used by research groups. There are approximately 200 PC's and a few Macs in the CS department, about 115 of which are used as personal or lab desktop computers. An additional server and 34 GNU/Linux workstations comprise our OS programming "Fossil" lab.

Access to Staff and Meeting Rooms

The PI has access to Computer Science Department system administrators and technical support staff who work to ensure that all departmental computing resources run smoothly. These technical staff will also provide support for any hardware, software, smartphones and technical resources acquired for this pro posed project. The PI also has access to support staff in the Computer Science office, assisting with arranging meetings and planning events, departmental sec retaries and department work study students. They also have access to office spaces and meeting rooms.

Campus Center and Meeting Rooms

The WPI Community has access to the Campus Center that provides a "physi cal, social and philosophical link between academic (and residential) portions of the campus." Completed in Spring 2001, the WPI 2 Campus Center, serves as a place for community, collegiality, socialization, and learning. The program for the Center includes work and meeting space for faculty, staff and student organi zations, conference rooms, mail facilities, dining food court, game room, college bookstore, large multipurpose facilities, visitor reception for campus guests, and lounges. The Events Office and Campus Center administrative office work as a team in scheduling facilities in the Campus Center. All of the meeting rooms have state of the art instructional media equipment installed in the rooms, and are sufficient to house any planned user studies, experiments or meetings planned to either gather data or evaluate preliminary versions of our prototype.

Campus Wide Computing Facilities and Services

Additional computational resources are available through the campus computer center, which maintains multiple high-performance clusters, more than a dozen file and web servers, and many hundred PCs for both general and course-specific use. As part of the Information Technology Division, the Computing and Com munications Center (CCC) provides the communications, computing, and stor age infrastructure, as well as the software utilities and applications to support the academic, research and administrative activities at WPI. The CCC contin ues to expand and adapt, incorporating new systems and technologies to ensure that WPI remains a leader in the use of technology in higher education. The computational resources available to the PIs maintained by CCC include mul tiple high-performance clusters, more than a dozen file and web servers, and several hundred PCs for both general and course-specific use. Numerous com puter labs, containing different kinds of computers, printers, and peripherals, are scattered around campus.The CCC maintains servers which are accessible from anywhere on campus. These servers provide a wide range of software and services such as e-mail, newsgroups, web pages, and network printing to members of the WPI community. The CCC is committed to the continuous maintenance, availability, and backups of all official computing equipment on campus. The CCC servers are located in WPI's primary server room, which is equipped with primary and backup power, environmental, and communica tion systems. Physical access to this room is strictly limited to current WPI systems administrators by means of electronic locks. Additionally, an alarm system that is constantly monitored by campus police has been placed to con trol access to the room and eliminate theft. The CCC also offers technology support services to WPI students, faculty and staff on a wide variety of systems and platforms. These support services include access and installation of the latest versions of software packages on all of the machines on campus, ranging from Microsoft Office Professional Plus 2010, Microsoft Office for Mac Standard 2011, Windows 7 (32 and 64 bit), to McAfee virus protection software. It also includes regular automated backups and continuous archival services. Last but not least, a 24 by 7 help desk provides technical support as well as instruc tions on many of the latest technologies to all members of the WPI community (http://www.wpi.edu/Academics/CCC/Help/).

WPI Library

The George C. Gordon Library is a state-of-the art facility http://www.wpi. edu/Academics/Library/About/ that contains a vast collection of physical and digital books and journals. It subscribes to numerous electronic journals in areas closely related to the proposed research work. It also houses collaboration and study spaces that this project can use for some meetings, if reserved ahead of time. The Tech Suites are work areas with cutting-edge technologies and are available by reservation to all WPI faculty, staff, and students. The Anderson Instruction Labs are computer training labs available for staff, but on evenings and weekends Lab A can be scheduled by groups. These resources are available to the entire WPI community.

1.2.5 Level of Effort

PI co-PI (General (ret.) Miera) 5 undergraduate students 1 graduate student (PhD) 1 consultant E. Doug Jensen, PhD. 1 consultant 1 consultant

1.3 Manner Contribute to Army's mission, how demon strated

We aim to show that the same amount of medical care can be deployed dif ferently, with the result that more patient welfare is retrieved. This can be in terms of a combination of better outcome per patient, or more patients saved.

The disruptive idea includes that the patient to be treated next is recom mended by the decision support system, with a different approach. Because the patient data is part of the situation, and the situational awareness can be more broadly distributed, the order in which patients are treated can be different that it would otherwise be.

In the case of scheduling and dispatching computer tasks, there are multi ple possible objectives. One possible objective is tasks per time, which would correspond to patients stabilized per time. A different objective is meet the most deadlines among the competing tasks. This objective corresponds to the most lives saved, because the result of treatment not being sufficiently timely is associated with non-survival of the patient.

We intend to demonstrate, over multiple scenarios with patients numbers, injuries, geographical distributions, the choices triage systems would make, as a function of the objective in use, and the set of patients included in the triage decisions.

We hope to show that by increasing the membership of the set of patients included in triage decisions (by including those whose data is being forwarded) , and the set of information about these patients, and varying the objective is use, that time utility based scheduling and dispatching will recommend a different order in which patients would be treated, and that the revised order will result in more patient welfare being retrieved by care.

1.3.1 Contribution to Army's mission

Our team includes personnel with experience as Army medics... They will rec ommend HCI functionality and interfaces ...

1.3.2 Demonstration

Methods To demonstrate the benefit of the scheduling and dispatching, sim ulations are run. The simulation generates randomized mass-casualty scenarios, with injuries sustained over a time interval and spatial extent. The simulation is parameterized by the resources available: number, stocking and location of field hospitals, numbers of transport vehicles of various capabilities.

Metrics The simulation estimates the number of patients who are able to be brought, alive, to a field hospital with resources allowing them to be saved. Two such estimates are made: one for present approach to triage, and the other using time/utility-based scheduling and dispatching.

For usability of the decision support software, this will be demonstrated by providing a (are there more than one?) prototype human interface.

Results

1.4 Research Facility

1.4.1 Local Storage of Data

1.4.2 Transmission of Data

1.4.3 Data Repository

1.5 Support

2 Schedule and Cost

Table containing phases, deliverables, milestones.

3 Addendum

E. Douglas Jensen, Ph. D

E. Douglas Jensen is internationally recognized as one of the original pioneers, leading visionaries, and accomplished engineers of distributed real-time systems– especially application-specific (notably dynamic) ones for the defense and space domains.

His seminal research led to the world's first deployed commercial product for distributed real-time computer control systems – the highly successful Honeywell H930 weapons control system for littoral combat ships. He subsequently made important contributions to the first commercial distributed computing product for industrial process control, the Honeywell TDC-2000. In 1977 he was the recipient of Honeywell's highest technical award for his contributions to the principles and practices of distributed real-time systems.

For the next eight years he was on the faculty of the Computer Science Department, and the Electrical and Computer Engineering Department, at Carnegie Mellon University. There he created and directed the largest academic real-time research group of its time. He lectured and consulted extensively for corporations, government agencies, and universities in 55 countries on every continent except Antarctica.

Subsequently he joined a startup and then held senior technology leader ship positions in several major companies. There, he advanced the theory and practice of application-specific hardware (e.g., GPU, FPGA, ASIC) augmented dynamic distributed real-time systems (which are important in the defense do main).

After he retired (from being a corporate employee) he is in high demand for lectures and consulting for industry, academia, and governments throughout the world. See his consulting practice time-critical-technologies.com. He limits his consulting primarily to classified combat platform (air, ground, ocean) manage ment and battle management (e.g., missile defense) for U.S. DoD contractors. During the Corona virus pandemic, much of his consulting is virtual and thus unclassified.

He has been an author of over 150 unclassified published scholarly papers thus far, They have been cited over 4133 times as of 1 January 2021 (Google Scholar). A list is at https://dblp.org/pers/hd/j/Jensen:E=_Douglas. (His classified work is not publically available.)

Specialties: Dynamic real-time systems, application-specific RTOSs and CPUs, cyber-physical systems, combat and sensor platform management, BMC2, net work centric warfare, ballistic and cruise missile defense. Active DoD security clearance.

James Ryan, Ph. D

We will find relevant work, including from our annotated bibliographies.

References

[1] Tactical evavutation proceedures

[2] Tactical field care and tactical evacuation care proceedures [3] Army combat trauma care in 2035.

Data should be continuously captured, retained, and for warded. Data that facilitates real-time care and guides review and change in the form of a trauma registry is critical. The Army should continue supporting, updating, and upgrading the trauma registry (the instrument panel). There is a need to break the paradigm of medical equipment procurement so as to not practice tomorrow's medicine with today's equipment.

[4] ASAMMDA health performance evacuation.

combat casualty care support systems

[5] ASAMMDA TCCC updates.

picture seems to show battlefield, voice says prehospital many times, is about the latest annual 11/2020, inability to follow commands for TXA, JSOM (heard not written) a conference in which papers appear,
prehospital blood is best, there are several initiatives, including ROLO (Ranger regiment uses), Valkyrie (MarineCorps uses), Vampire, FORSCOM, (other DoD)
blood to the front line, walking blood bank
(determining blood type, for informing transfusion) at point of injury
monitor for re-emergence of evisceration after initial reduction monitor for bleeding at evisceration
care under fire, care under fire/thread

[6] Automated monitor detects life-threatening bleeding during trauma trans port.

portable computer system that analyzes patient vital signs dur ing emergency transport to detect life-threatening hemorrhage. Automated system “successfully identified 75 to 80 percent of patients with life-threatening bleeding, compared with 50 per cent who were identified by standard clinical practice.

[7] The blue force tracker system.
Unit locations and movements, along with intelligence data on enemy forces and battlefield conditions, are distributed over a satellite communications network that the Army calls FBCB2.

[8] casualty care course.

Mass Casualty (MASCAL) events,

[9] COSMED is proud to introduce K5, the 4th generation of the most popular wearable metabolic system, and a breakthrough in the field of exercise physiology and human performance assess ment. The K5 is the most innovative and versatile metabolic system ever created. The K5 reaps the benefits of more than 25 years of experience with metabolic systems. It features a list of new and unique characteristics that expand the scope of metabolic testing from clinical exercise testing to performance assessment.

[10] Defense health agency procedural instruction.

Implementation Guidance for the Utilization of DD Form 1380 [11] Hands free for greater casualty focus.
MEDHUB evaluation and feedback

[12] Joint battle command–platform.

JBC-P will be interoperable with the Nett Warrior handheld de vice, managed by Program Executive Office Soldier, delivering situational awareness capabilities to dismounted Soldiers. Joint Battle Command-Platform (JBC-P), fielded to the first unit equipped in May 2015, is the Army’s next-generation, friendly force tracking system, equipping Soldiers with a faster satellite network, secure data encryption and advanced logistics.

[13] Military-designed vital signs monitors could boost remote care.

monitor travels with the patient, meaning they don’t need to be transported in specialized medical vehicles or helicopters equipped with medical devices. Instead, patients can be trans ported in anything with wheels or rotors. New monitor will be included in a package called the Automated Critical Care Sys tem (ACCS) System can monitor and store patient data contin uously, no matter how remote the location, and then transfer that data to other medical record systems when internet access becomes available.

[14] Next-generation incident command system.

NICS is the incident map, which displays real-time information, such as incident perimeters, evacuation zones, weather condi tions, and images from the scene. The information displayed on the map is gathered from external data sources and inputted by emergency personnel using either the web-based system or the accompanying mobile application.

[15] rethinking-how-the-army-network-can-help-with-battlefield-injuries.

The golden hour, the first 60 minutes after a battlefield wound, is considered the most critical period for soldiers. To maximize that time, a new effort is automating the transmission of medi cal information of soldiers en route to the hospital.
In many cases, when a medevac crew arrives, they discover more casualties than previously reported and the only way to commu nicate back to the hospital was a single channel radio. Officials at Fort Detrick told C4ISRNET that this kind of voice transmis sion is not the best way to communicate. For one, the hospital staff might not accurately write down the message and two, the medic in the vehicle is on the radio and not treating patients. Together, this means the hospital might not be prepared for the increased number of patients. To solve this problem, MED HUB automates the process by which patients' vitals are trans mitted to the hospital. This, in turn, allows the hospital staff to have a better count of wounded soldiers coming in, which makes them better prepared for triage. The system works by transmitting data over the blue force tracker network using ex isting programs and equipment. It relies on NetWarrior devices and software that is used now to provide battlefield situational awareness. The system is connected to multiple wireless patient monitors housed in the medevac vehicle — either a helicopter or a ground vehicle — and sends the patient's condition, injury and vitals every two minutes.
Additionally, MEDHUB is designed so that if certain condi tions are met — such as a certain percentage increase in blood pressure — it will immediately transmit that data back to the hospital. By automating this process, medics don't have to log injuries and vitals by hand. In the fog of war, injuries haven't always been logged as accurately as they could be when trans porting patients, officials said. For hospital staff, they can now take advantage of a dashboard, a repurposed artillery system running on Mounted Family of Computer Systems (MFoCS), where the new patient information is sent.

[17]6 tactical combat care collection.
[18] *Tactical Combat Casualty Care (TCCC) Guidelines for Medical Person nel*.

Triage casualties as required.
iTClamp to neck implies desirability of frequent airway monitoring and evaluation of expanding hematoma that may compromise airway
monitor hemoglobin oxygen saturation to help assess airway patency
avoid overpressurization, especially during TACEVAC on an aircraft with the accompanying pressure changes
There is an obvious hissing sound as air escapes from the chest when NDC (decompression of pleural space in suspected tension pneumothorax) is performed (this may be difficult to appreciate in high-noise environments), or Hemoglobin oxygen saturation increases to 90% or greater (note that this may take several minutes and may not happen at altitude), or A casualty with no vital signs has return of consciousness and/or radial pulse.
it is possible to monitor the wound closely for bleeding; –This is one of multi-part condition for being able to replace a tourniquet with a hemostatic or pressure dressing
Every effort should be made to convert tourniquets in less than 2 hours if bleeding can be controlled with other means
under an approved command or theater blood product admin istration protocol – Is theater a field hospital, or preHospital? Here is a set of useful criteria: Continue resuscitation until a palpable radial pulse, improved mental status or systolic BP of 100 mmHg is present. – Can we think about how we would sense these?

Transfusion should occur as soon as possible after life threatening hemorrhage in order to keep the patient alive. – sounds like preHospital, but how are supplies of cool, screened O blood available? Is this a case for drone delivery?
absent breath sounds, and hemoglobin oxygen saturation ¡ 90% support this diagnosis–to be sensed
refers to on evacuation platform
Initiate advanced electronic monitoring if indicated and if monitoring equipment is available – drone delivery?
For all casualties given opioids, ketamine or benzodiazepines – monitor airway, breathing, and circulation closely.– sensors? Monitor for respiratory depression – sensing
determine if the casualty is decompensating. – sensing
If that fails, provide ventilatory support with a bag-valve-mask or mouth-to-mask ventilations – used
Hypothermia – monitor closely as exposed abdominal contents will result in more rapid heat loss – sensing
Aggressively monitor airway status and oxygen saturation in such patients – sensing
Resuscitation on the battlefield for victims of blast or penetrat ing trauma who have no pulse, no ventilations, and no other signs of life will not be successful and should not be attempted. b. However, casualties with torso trauma or polytrauma who have no pulse or respirations during TFC should have bilateral needle decompression performed to ensure they do not have a tension pneumothorax prior to discontinuation of care. The procedure is the same as described in section (5a) above. — (5a) is the needle decompression mentioned above with "wait several minutes". Thus we can tentatively conclude that that waiting is occurring on the battlefield, prior to evacuation to a field hospital.
Provide leadership with casualty status and evacuation require ments to assist with coordination of evacuation assets

[19] title.

The prototype system consists of a small sensor hub that is mounted on a commercial heart-rate strap that is worn over the chest. The sensor hub measures heart rate, skin temperature, and body movement, and employs USARIEM algorithms that use those physiological measurements to estimate a soldier's strain index. The hub sends this information wirelessly to a team leader's smartphone, which is modified with a Laboratory-developed communications device approved by the U.S. Army Spectrum Management Office.

[20] USAMMDA fast tracks MEDHUB device to warfighters.

telemonitoring.
reduce the burden on medics and to alert and prepare a hospital for en-route patients through telemonitoring
Field hospitals lack situational awareness of incoming patients' injuries and treatments because of limited communication networks between ambulances and hospitals. The effects are felt at the hospital when the medic must provide a short verbal report in a noisy, high-stress environment at time of arrival. These short verbal reports may not be comprehensive and are not available for further reference by the attending physician.
Medical Hands-Free Unified Broadcast (MEDHUB)
MEDHUB is an automated electronic medical documentation and communication system designed to improve the way medics and hospitals share patient information, such as vital signs, injuries and treatments, during medical evacuations.
With MEDHUB, medics can use a tablet to complete a Tactical Combat Casualty Care Card electronically.
MEDHUB alerts the hospital before patients arrive, earlier than the current radio call, which gives hospital personnel extra time to plan by gathering the supplies and manpower necessary to

effectively treat the patients once they arrive. MEDHUB simplifies patient care by providing a vital signs monitor for every patient, so the medic does not have to switch monitors between patients, and it provides additional drug safety through dosage calculators and visual cues for the medic. Effective: We must deliver what warfighters need, when they need it, in a timely and affordable manner. Innovative: We must create and cultivate a culture that front-loads smart risks through iteration and prototyping. Agile: We must be willing to fail early and responsibly, and learn from our failures and successes. We must be creative and not become victim to a ”that is not how we do it here” mentality. Unified: We must become ”one team” with a laser focus on creating speed through shared goals and understanding, disciplined initiative, enabled decision-making at the lowest level, and delivering valued outcomes for the Army.

[21] Lamia CHAARI, Audace MANIRABONA, and Saadi BOUDJIT. Inves tigation on healthcare monitoring systems: Innovative services and appli cations.

[22] Dr Kanta D Devangavi. Medical monitoring application using wireless sen sor network. *VTU PG Center Bengaluru region, Chikkaballapur-572101*.

[23] TATRC Expands its Role. Tatrctimes.

the new DoD electronic health record system, MHS Genesis Army Warrior Care and Transition System (AWCTS).

t he has a need to introduce a mobile component for AWCTS and we are actively working with him now to see how we can utilize mCare to bridge his gap

The Telemedicine and Advanced Technology Research Center’s (TATRC’s) Health Information Technology Center (HTIC) has been examining the promise of Blockchain technology for the past year. The time is ripe for the Defense Health Agency (DHA), Defense Healthcare Management Systems (DHMS), Army Medicine, and others to consider funding Blockchain pilot studies.

Open source Blockchain initiatives, such as Linux Foundation’s HyperLedger Initiative on GitHub, are accelerating innovative Blockchain technologies.

Blockchain can create an extremely secure, fully transparent, decentralized, longitudinal, life-long, digital accounting ledger, which points to all of a patient’s health and fitness transac tions. It supports distributed integration of healthcare infor mation across a number of stakeholders. Although 75Records (EHRs) to collect health information, these commercial EHRs were never designed to collect a patient’s longitudinal, life-time data, and may now contribute to a fragmented system of health data. With Blockchain, a patient or his/her designated author ity can permit designated parties access to discrete information controlled by this ledger, for a designated amount of time (con ditional privacy). In addition to enabling secure, interoperable HIE, Blockchain can prevent health data breaches and being held hostage to Ransomware; enable claims fraud detection, Beth Israel Deaconess Medical Center, Boston, MA, in partner ship with the MIT Media Lab and local VA Medical Center VA, has created a proof of concept Electronic Health Record (EHR), known as “MedRec,”

AAMTI Featured Project: Effectiveness of Lifesaving Resusci tative Interventions and Damage Control Surgery in Blackout Conditions using Night Vision Technology

Point of injury care remains a focal point in military medicine. During special operations and conventional conflicts, military medical providers are frequently required to perform life-saving interventions under hostile conditions in low-light environments. Definitive surgical care and invasive resuscitative procedures are often delayed until a white light environment is permissible, po tentially postponing lifesaving care. A team of researchers at Madigan Army Medical Center (MAMC) sought to determine if night optical device (NOD) technology could enable surgical capabilities in blackout conditions.

A variety of procedures were performed during this study, from basic, resuscitative measures such as tourniquet application, placing peripheral and central venous access catheters and intra osseous devices, to advanced maneuvers such as exploratory laparotomy, splenectomy and placement of a resuscitative en dovascular balloon occlusion of the aorta (REBOA) device.

109s) p=0.010. The results of the study suggest life-saving in terventions can be safely and effectively performed in blackout conditions using NODs. Thus, this technology has the poten tial to push surgical capabilities closer to the point of injury, possibly saving Soldiers' lives. Surgeons attached to special op erations units may be able to have more robust surgical capa bilities in blackout conditions with the use of NODs. Based on a post-study survey of the surgeons involved, 100can be pushed to medics, corpsmen and mid-level providers with appropriate training for point of injury care. LTC Matthew Eckert stated"... The ability to safely and effec tively perform these procedures in potentially hostile forward lo cations may be a game changer for preventing potentially avoid able deaths on the battlefield."
This year, two of TATRC Labs joined forces and teamed to gether. TATRC's Operational Telemedicine (Op-Tmed) Lab and the Biotechnology High Performance Computing Software Applications Institute (BHSAI), began a collaborative effort to implement BHSAI's Automated Processing of the Physiologic Registry for Assessment of Injury Severity (APPRAISE) sys tem on a mobile device. APPRAISE, is an artificial intelligence based system that can alert medics when trauma patients are in need of massive blood transfusions without any human interven tion. It collects and analyzes, in real time, vital sign information from the patient during pre-hospital transport. It then uses the results of that analysis to determine if the patient will need a blood transfusion before the patient arrives at the hospital with 78 percent sensitivity and 90 percent specificity, within 10 min utes of the start of monitoring.
the Propaq and Tempus Pro via the UWB protocol, as well as expanding the capability to display multiple patients and their APPRAISE scores on the same screen and post to multi ple electronic DD1380 cards, thereby enabling medics to triage multiple patients more effectively in mass casualty scenarios. TATRC's Operational Telemedicine Lab Manager, Dr. Gary Gilbert stated, "The Army NETT Warrior and SOCOM Ad vanced Tactical Android Kit EUDs and supporting equipment are already being fielded to designated Role 1 medics as stan dard combat gear. If the Boston MedFlight tested APPRAISE algorithm receives FDA clearance and is integrated on to those EUDs along with appropriate patient monitoring sensors, the Battlefield Airmen Trauma Distributed Observation Kit (BAT DOK) application with a transmittable DD1380, and the PM JOMIS MCC (Mobile Computing Capability), our battlefield capability for triage, monitoring, and treatment of combat ca sualties prior to reaching Role 1 clinics and aid stations could be significantly upgraded without adding additional weight to combat loads." Previously, APPRAISE had been tested in civil ian markets on ruggedized PCs on board medical evacuation helicopters operated by Boston MedFlight, which services Harvard University Trauma Centers. By implementing APPRAISE onto a NETT Warrior type Android phone, the capability to detect early life threatening hemorrhage, became portable and integrated with the MC4 electronic DD1380 application so that users could document timestamped APPRAISE scores on a pa tient's record. In addition to having the APPRAISE score dis played on the electronic DD1380 card application, TATRC's Op-T-med Lab also enabled a Visi Mobile patient monitor to wirelessly transmit the vitals data to the phone via Ultra Wide Band (UWB) secure wireless protocol to eliminate wires while reducing interference and detectability. Future efforts will in clude integrating data input to the APPRAISE algorithm run ning on NETT Warrior type Android End User Devices (EUDs) from additional monitoring systems such as Dr. Jaques Reif man, Director of TATRC's BHSAI added, "The APPRAISE has numerous advantageous features that will facilitate dissem ination of the technology. For example, it uses standard vital signs as inputs (heart rate and blood pressures) that are readily available and familiar to medics. Also, the system assesses the reliability of the vital signs in real time, making sure that only those deemed to be reliable are used. Essentially, what AP PRAISE does is to automate what experienced clinicians do: look at vital-sign patterns and identify those associated with life-threatening hemorrhage versus those associated with normal fluctuations."

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> The U.S. military currently utilizes unmanned aerial vehicles (UAVs) for reconnaissance and attack missions; however, as combat environment technology advances, there is the increas ing likelihood of UAV utilization in prehospital aeromedical
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> The emergence of more complex Prolonged Field Care in austere settings and the need to assist inexperienced providers' ability to treat patients create an urgent need for effective tools to support care. We report on a project to develop a phone-/tablet-based decision support system for prehospital tactical combat casualty care that collects physiologic and other clinical data and uses machine learning to detect and differentiate shock manifestation.
> Machine learning algorithm methods included development of a model trained on publicly available Medical Information Mart for Intensive Care data, then on de-identified data from Mayo Clinic Intensive Care Unit.
> We expect the Trauma Triage, Treatment, and Training Decision Support system will augment a medic's ability to make informed decisions based on salient patient data and to diagnose multiple types of shock through remotely trained, field deployed ML models.
> the need to assist inexperienced providers' ability to diagnose
> patients compels development of tools to assist diagnosis and treatment using a systematic approach They cited two here.). We report on the first year of a 2-year study to develop a Nett Warrior phone- and tablet-based decision support system (DSS) for prehospital tactical combat casualty care (TCCC) that is able to detect and differentiate shock using only vital signs data.
> The Trauma Triage, Treatment, and Training Decision Support (4TDS) project consists of two parallel design and development efforts: the 4TDS system and the machine learning (ML) algorithms.
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Lincoln Laboratory has developed a novel metabolic fuel model and low-cost breath sensor for measuring, tracking, and enhanc ing metabolism. The model can predict key metabolic state parameters, including blood glucose levels, available glycogen stores, nutrient substrate utilization, and fat accumulation or depletion, for a given diet and activity profile. It can also pre dict healthy metabolic responses to a variety of dietary inter ventions and the onset of medical conditions, such as type 2 diabetes and excessive fat accumulation. The model suggests that the measurement of key metabolic parameters, such as res piratory quotient and energy expenditure, can provide insight into metabolic health and improvements in athletic performance

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and endurance.
The U.S. military has an interest in comprehensive metabolic measurement and tracking systems for optimizing the perfor mance of soldiers under demanding physical conditions and for maintaining soldiers' metabolic health and wellness. It is in this context that Lincoln Laboratory has been developing a novel metabolic model to predict how the body will respond to changes in dietary intake and activity level. The body's re sponse can vary from person to person, with training, and over time; this variability requires measuring individual metabolic parameters to fully personalize the model.
an RQ of 0.7 implies that all of the calories are supplied through fat combustion, whereas an RQ = 1 implies that calories are being supplied exclusively from glucose. Figure 8 implies that resting RQ is driven primarily by the available mix of circulating macronutrients, whereas the preferred fuel (fats versus carbohy drates) during exercise is driven primarily by exercise intensity [55].

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