DEVELOPMENT OF AN INJURY PREDICTION MODEL

Final report Phase II, EEC contract NL-5

R-80-55

T.Heijer

Voorburg, 1980

Institute for Road Safety Research SWOV, The Netherlands

1. Introduction

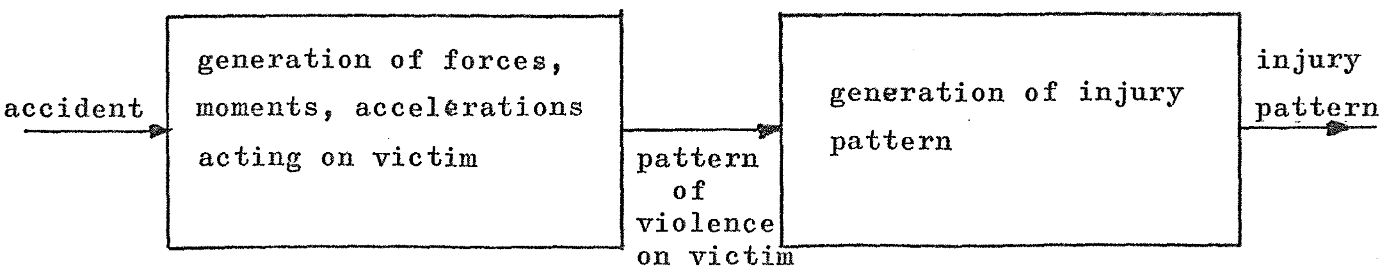
The increasing interest in the research field of biomechanics or, more specificially, injury mechanics, in the past few decades has already produced a great amount of data.
Various, more or less succesful, attemps have been made to integrate this mass of data into consistent theories for injury mechanisms, sometimes resulting in relatively simple injury criteria.
Since it is common knowledge that the existing injury criteria yield predictions that are only partially consistent with "reality", we feel justified in making an other attempt; the hereby presented project should be considered as such.

2. Basic assumptions and limitations

The first limitation is that we only consider those injury mechanisms that are brought about by external violence to a victim, thus excluding "natural" diseases.
A more important limitation is that we must confine ourselves to the well investigated areas of injury mechanics (e.g. head injuries) since we do not have research facilities of our own.
Furthermore, research of the presented kind is only practical if we can assume that any injury process is mainly influenced by limited if possibly large, number of recognisable and measurable parameters.

3. The injury process

Let us consider an injury generating process as applied to a single victim.
Such a process may be divided in the following stages:



The first stage of the thus divided process has been and is a subject of extensive research, sometimes resulting in quite accurate mathematical models (the IW-TNO developed, SWOV sponsored MADYMO-models for instance).
It is clear that in this stage already certain characteristics of the body of the victim play an important part in the generation of violence.
A number of those characteristics such as: linear dimensions, mass, mass distribution, force-displacement properties of various tissues, are relatively easy to get; other properties, like moments of inertia of parts of the body, resistive joint torques etc. are harder to obtain.
Nonetheless, for an accurate insight into the pattern of violence on a single victim we need to quantify all those characteristics simultaneously.

The same reasoning goes for the second stage of the process: the generation of injury.
The difference with the first stage lies mainly in the fact that the definition and evaluation of important characteristics is much more difficult, if at all possible; examples of such parameters are: mechanical properties of bones, blood vessels, brain tissue, tissue of the liver etc.
Furthermore, factors as fatigue, sports training and other hardly measurable factors may play a role in injury generation.

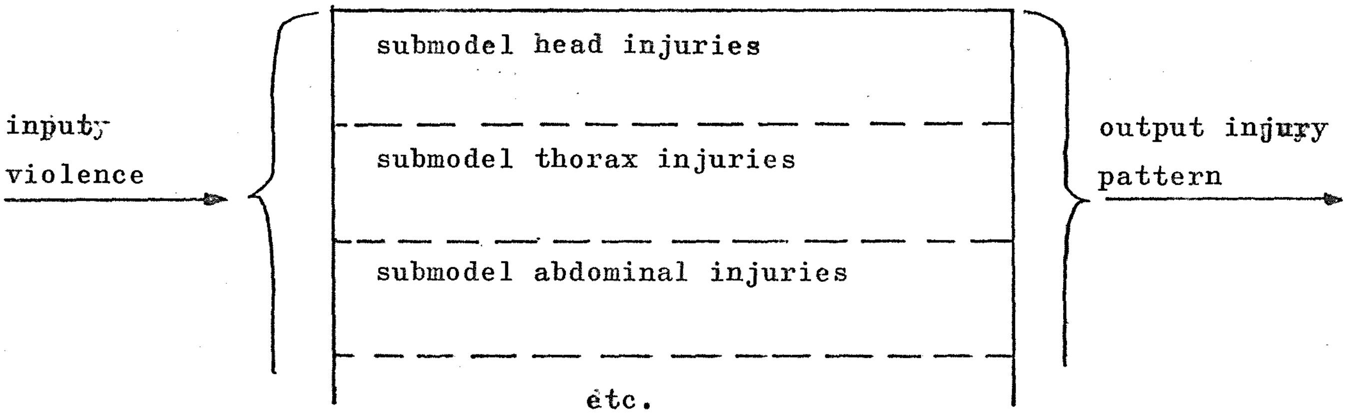
Modelling the injury process

For modelling purposes the division in the injury process is a convenient choice; as said, the first stage is already well looked at by research and, to obtain data and patterns of violence on an arbitrary subject, we may make use of various mathematical models available.
Moreover, violence data may also be obtained by dummy tests.
Thus, our attention should mainly be given to the second stage of the process.

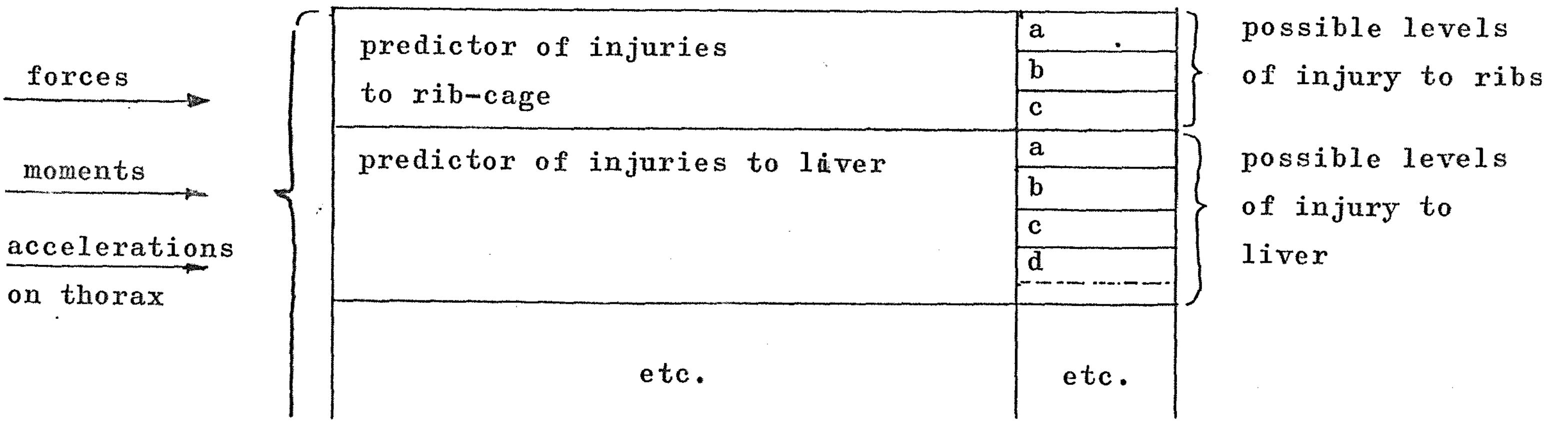
In the following, we will give a step by step accounting of the considerations that may lead to a model for this stage.

3a. General considerations

The actual injury process is continuous in many respects. Violence may be applied to any point of the body, resulting in injuries of (continuously) varying degree.
In our model, however, those conditions are somewhat hard to handle and the most common solution to such a problem is, to divide that problem in classes, subclasses etc. to make it more accessible. Thus, making some choices for divisions, the overall model may be divided in submodels for various parts of the body like this:



Within each submodel, especially at the injury output side , the injury prediction process can also be divided into discrete blocks, mainly to provide a means for differentiation in injury categories and injury levels.
For example, the thorax-injury submodel may look as follows:



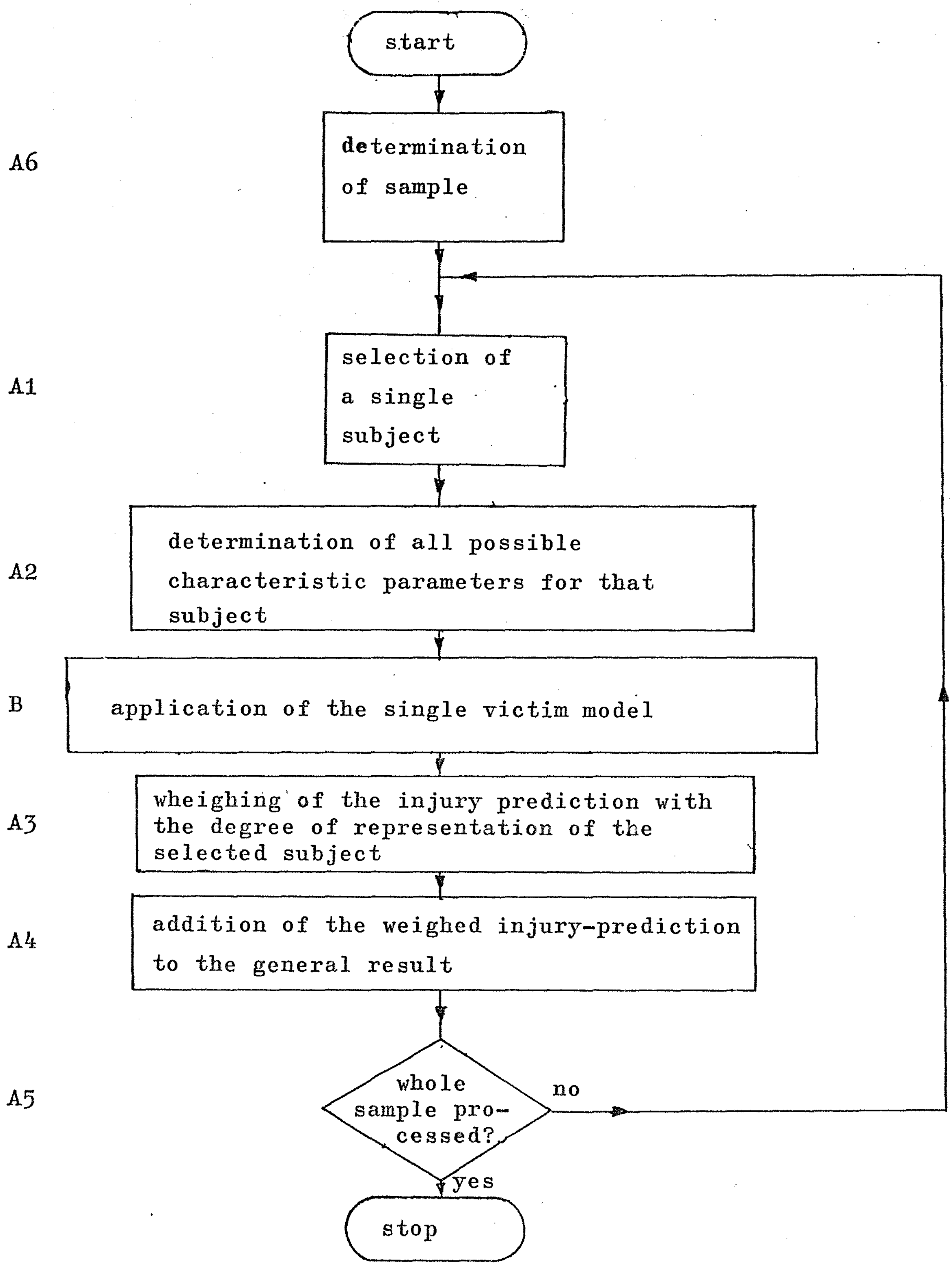
In this way, the model consists of a voluntary number of submodels, each in its turn divided into predictor modules for injury categories. The output of a predictor module consists of a vector in which each element, representing a certain injury level, is assigned the probability of occurance of that level.
(N.B. If we assume that we can quantify all significant parameters, the accuracy of prediction is 100 %, which means that only one element of an output vector is assigned a value 1 while all other elements must be 0).

Observe, that the use of submodels and predictor modules makes a highly flexible model; we "only" have to establish a general processing routine for one such a submodel-predictor combination and apply this routine to all combinations no matter how many there are.
Thus the model can be easily expanded.

3.b. Single victim model and generalisation

So far we have only considered the modelling of an injury process of a single subject.
Such a model may be applicable in a limited way but it is, itself, not suited for use as a general prediction tool.
Essentially, what we have to do to generalise the results is to apply the model a number of times to different subjects that are chosen so as to form a representative sample of the considered population.
This repeated application of the model can be put into a "flow chart" as drawn on the next page.
In this flow chart there are two separate functions:
A: the "bookkeeping": this involves all manipulations to provide input for injury prediction and to process the output of the predictions (functions are marked A1 through A6).
B: the model which provides the actual prediction (marked B).

In the following we will consider the two functions separately.


start
A6
determination of sample
A1
selection of a single subject
A2
determination of all possible characteristic parameters for that subject
B
application of the single victim model
A3
wheighing of the injury prediction with the degree of representation of the selected subject
A4
addition of the weighed injury-prediction to the general result
A5
whole sample processed?
no
yes
stop

4. Functions of the generalised model

Generally speaking, it is impossible to quantify all relevant parameters that govern the outcome of an injury process even for a single subject.
Moreover, if there are such parameters that can be measured accurately, it is very difficult to obtain those parameter values for a whole population.
All this imposes at least two important (if trivial) limitations to the modelling activities:

a. certain types of injuries will not be predictable at all;
b. the prediction of other injuries will generally be based on limited information which renders the prediction uncertain.

The effect of the first limitation is clear, the effect of the second one will now be considered.

4a. The model function

The single victim model, as introduced in chapter 3a with its divisions and subdivisions is already adapted to handle "uncertain predictions".

The main effect of uncertainty of prediction versus 100 % certain predictions is, that the output vector of each predictor module will contain a probability factor P_i $(0 \leqslant P_i < 1)$ in each element i of the vector. (For consistency, the sum of all elements of any injury probability vector must be 1).

At this moment it is impossible to select a way by which the probability factors will be calculated, since that depends on the availability and accuracy of parameter data (the first literature studies are not yet completed).
Moreover, also depending on parameter data, the method of calculation of the probability factors may vary for different predictor modules. However, a number of ways can be hypothesised; see appendix A for examples.

4b. The "bookkeeper" function

From the flow chart in chapter 3b we see that the bookkeeper function consists of 2 major tasks:

1. selection of a subject and collecting all data pertaining to that subject;
2. updating of the output injury-vectors with the results of the model function.

Since the first task implies data transmission rather than data processing, it will not be influenced by the degree of certainty (the second limitation) of the data.

The second task does imply data processing; however, now it concerns the output vectors of the model, consisting of non-dimensional probabilities (= simple real numbers).
So this task, too, is not affected by the second limitation.

All this implies, that we need to construct a bookkeeper function only once and we will not have to change that function if (through research) more extensive data about the injury-process become available.
In fact the only part of the overall model that needs adaptation then, is the "model" function itself.

Let us now consider the separate tasks of the "bookkeeper" more closely, and let us start with the simplest task:

Updating of the output vectors (2)

This task is probably best illustrated by an example:

Assume: as certain subject from the sample represents 0,8 % of the total considered population.
Assume furthermore: the output vector of one of the predictor modules "scores" as follows:

Predictor module X (4 injury-levels)

injury level	probability of occurrence for selected subject
I	0,1
II	0,45
III	0,25
IV	0,2 +
	1,00

Now, since the predicted probability of injury-levels only applies to the selected subject = to the represented percentage of the population, the contribution to the general output vector for injury type X will be:

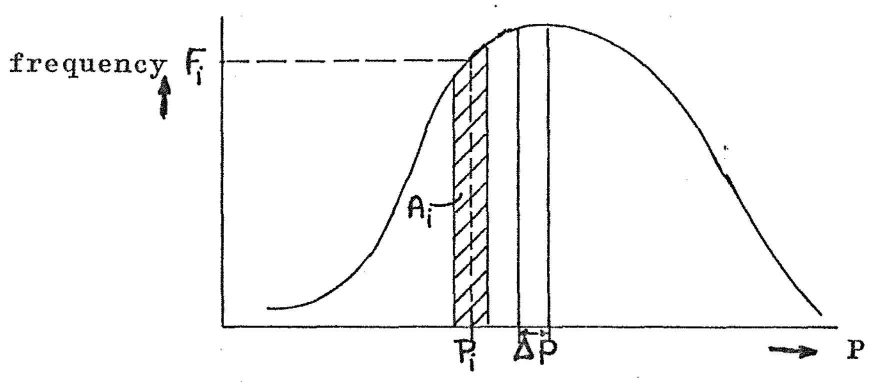
General output vector for injury X

injury level	probability of occurrence for considered population
I	+ 8/1000* 0,1 = + 0,0008
II	+ 8/1000* 0,45 = + 0,0036
III	+ 8/1000* 0,25 = + 0,0020
IV	+ 8/1000* 0,2 = + 0,0016 +
	0,0080

Thus, the output vector of all predictor modules is weighed with the degree of representation of the subject and added to a general output vector or, before weighing and addition, first be weighed by a diagnostic criterion like AIS. (See chapter 6).

Task 1 selection of a subject/data collection

The tasks of determining a sample, selecting a subject from that sample and collecting the data pertaining to that subject must all be considered as operations upon the simultaneous distribution of the parameters for the considered population. (See appendix B for amplification on the simultaneous distribution).
The nature of those operations is best illustrated with a simplified example, in which the simultaneous distribution function of n parameters is replaced by a single distribution of one parameter P.

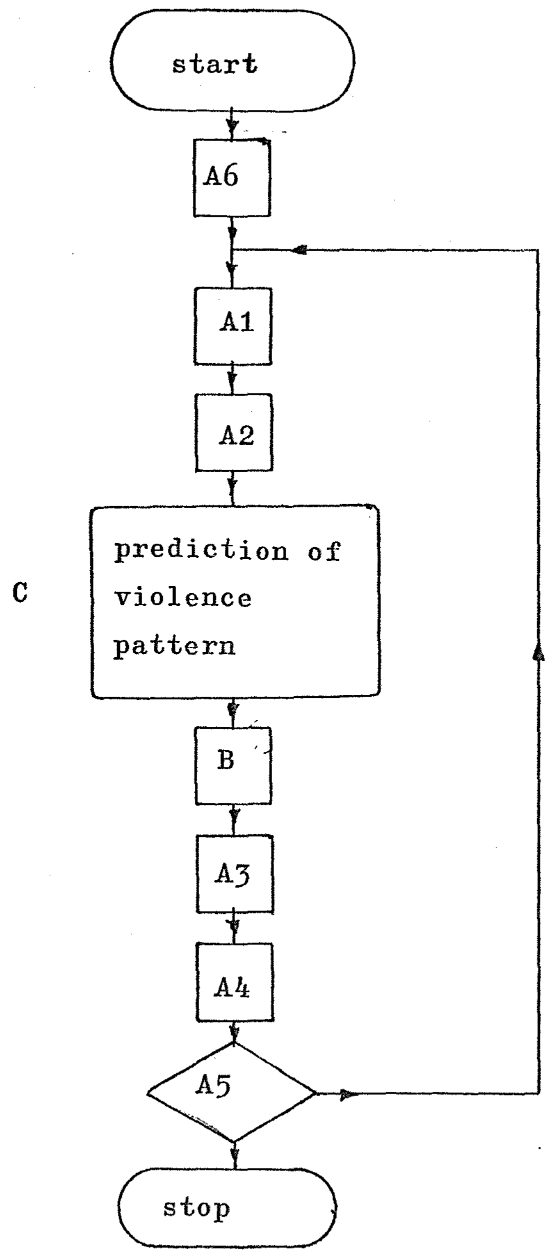


Let us say that the curve represents the distribution function of P as measured for I = 10,000 individuals.
We may want to represent those 10,000 by N selected individuals, each in a certain group, so that each member of the group has a value of P sufficiently close to the selected value to be acceptable according to a certain criterion.
A very common sampling technique which we can adopt, is to devide the P axis in N intervals of equal width.
Thus the area below the curve is divided into N small fields.
We can calculate the area of a certain field by $A_i = \Delta P * F_i$ in which F_i represents the average frequency value associated with the field and P_i the average value of P.
Since $A_i * I$ ($= A_i * 10{,}000$) represents the number of individuals with a parameter value of P in the considered field, $100\ \% * A_i * I/I = 100\ \% * A_i$ denotes the degree of representation for this field.
In this way we assign a degree of representation to each sample.
It is clear that the way, by which we determine a representative sample in the case of the simultaneous distribution is far more complex. Nevertheless, the basic considerations are the same.

4c. <u>The overall model structure</u>

In most considerations concerning the construction of a model for injury prediction we have assumed that a certain pattern of violence works on all members of a population.
However, already in chapter 3 we have seen that this pattern of violence may also be dependent upon certain characteristics of the victim.

So if we want to attain the original goal: to be able to predict injury patterns that are evoked by a distinct type of accident, we must take into account that the violence, sustained in such an accident may vary.
This effects the model flow chart in so far, that between the determination of parameters and application of the injury-prediction model a phase must be incorporated in which the pattern of violence is calculated.
Referring to chapter 3b the flow chart becomes:



Although this incorporation is correct theoretically, it is not always practical.
If we obtain the prediction of the pattern of violence by means of a mathematical model, it may be possible to construct a continuous chain of "bookkeeping and prediction" within a single computer model structure. If, on the other hand, the prediction of the pattern of violence is obtained by dummy tests, the whole model becomes fysically disjoint.
Therefore, it can be practical to maintain the separation that we introduced in the injury process chapter 3; first predict the pattern of violence: to this end we need a sample of the simultaneous distribution of only those parameters that are relevant to violence prediction.
- second: prediction of the injury pattern as outlined in chapter 3b; however, now we must take into account the restrictions, in selection of the parameters, that the sample in the first phase may impose on us.
If, for instance parameter α is necessary in the first as well as in the second phase, we must realise that in the first phase a number of values (samples) for α already have been chosen, so if we determine a sample of parameters in the second phase, parameter α must have the same values as in the first phase and cannot be chosen freely.

Note: If we employ dummy tests as a predictor for patterns of violence with for each type of dummy an inherent selection of a number of parameter values we must realise that subsequent prediction of generalised injury patterns can only be valid for those subjects in a population that have approximately those parameter values in common.

5. Input data for the models

In the previous chapters we always assumed the availability of data on the simultaneous distribution of parameters.
However, those data are not readily available from litterature.
In fact, a lot of publications on injury research normally give ample data on the investigated injuries, but otherwise commonly only the most easily accessable parameters like age, sex, mass and body length.
Moreover, the human material available for research can hardly be called representative for a whole population since it concerns a majority of cadavers of older people.
And, apart from that, there are the data on animal experiments with theire own peculiar scaling problems.

All this makes, that the construction of a database for the prediction model in itself will be a complicated iterative process in which:

a. the available data must be fitted into a hypothesised and approximated form of simultaneous distribution;
b. the model output on basis of this hypothesis must be checked against "reality";
c. the hypothesised form must be adjusted as a result of that check.

Since it is clear from the previous chapters that parts of the model structure are influenced by the nature of the input data, it will be clear that model construction and construction of the database are inseparable activities; thus in the iterative proces follows a phase:

d. revision of some parts of the model.

6. Interpretation of the output of the model

In chapter 4b, under the heading: "updating of the output vectors", we summarised briefly what steps can be taken once we have calculated the output vectors of all predictor modules for one selected subject. We will now examine those possibilities.

- Direct addition to a general output vector

In this case a general output vector contains all types of predicted injuries and their subdividions (see chapter 3a).
After addition of the predicted probabilities for all samples, this vector still contains a probability factor in each element, however, now valid for the whole population. This vector gives us information about the occurrence of the injuries separately and does not tell us which types of injuries occur simultaneously; in this way the information about the injury patterns of the individual samples is lost.

- Diagnosing before weighing and addition

This possibility gives us more information but is considerably more complex.
We start at the moment that we have predicted the injury probabilities for one sample, before we weigh those probabilities with the level of representation of the sample. At that moment we have information about the combination of injuries.
How we proceed in this case is again best illustrated by an example. Say that we have a version of the model that predicts 4 types of injury; injuries are: Ia, Ib, Ic and Id. Each type of injury has only 2 severity classes: 1 = no injury, 2 = injury.

Say that after the processing of a certain sample, the output vector looks like this:

injury type	class	probability
Ia	1 2	0 1
Ib	1 2	0 1
Ic	1 2	.3 .7
Id	1 2	.4 .6

First we apply the AIS criteria to those injuries that are predicted with certainty: Ia and Ib.
Let us assume that, on basis of those two, AIS severity 2 is calculated.
In addition the following combinations are possible:

Ic ↓ class / Id → class	1	2
1	.3 * .4	.3 * .6
2	.7 * .4	.7 * .6

Resulting possibilities for AIS evaluation with their respective probabilities are:

injuries	combination of classes			
	nr 1	nr 2	nr 3	nr 4
Ia	2	2	2	2
Ib	2	2	2	2
Ic	1	1	2	2
Id	1	2	1	2
probability	.12	.28	.18	.42

We can assign AIS values to all these possibilities assume:

combination nr	AIS
1	2
2	3
3	3
4	4

Assume furthermore, that the degree of representation of this sample is: 0.05.

If we now define a general output vector it must be a vector of only 6 elements: one element for each level of the AIS.
We can calculate the contribution of the example to the output vector in the same way we did in chapter 4b:

possibility nr	probability	AIS	contribution to =	
1	.12	2	.12 * .05 = 0,006	
2	.28	3	.28 * .05 = 0,014	} 0.023
3	.18	3	.18 * .05 = 0.009	
4	.42	4	.42 * .05 = 0.021	

In this way, the output vector does give us information about the severity of simultaneously occurring injuries, at the cost of a considerable increase in the number of calculations.

Appendix A

Internal structure of a "predictor module"

As indicated in chapter 4A, the nature and precision of available data determines largely the nature of the prediction technique.
That technique may be a physical calculation or a purely stochastical one or any mixture of both.
The difference between the two is best illustrated with a few examples.

a. (pseudo) physical model technique

Say that we want to predict a femur fracture, due to transverse forces somewhere one the bone.
Assume that we can obtain the following data (remember that in this stage of the model we have already selected one subject by a sampling technique).

- location of the points of application of the forces
- length of the bone σ m
- tensile strength of the bone
- moment of inertia and max. diameter of cross-section of the bone, I and d resp.

Under these conditions the prediction process is straight forward:

. from the forces on the bone we calculate a bending moment M
. we calculate a tension σ_s on the surface of the bone by:

$$\sigma_s = \frac{M.d}{2.I}$$

. we calculate the ratio σ_s / σ_m .

If $\sigma_s / \sigma_m \leqslant 1$, no fracture will be predicted.
For $\sigma_s / \sigma_m > 1$ a fracture will be predicted; we might even differentiate the severity of fracture as a function of σ_s / σ_m
In any case, the calculation yields an unambiguous result and the output vector will therefore contain zero's, exept for one element, representing the calculated fracture severity; this element will be assigned the value 1.

b, Stochastical modelling

If we know too little of the causal relations between violence, body characteristics and sustained injuries but still have date on violence and subsequent injuries, we may construct a transition matrix type of prediction.

Say, for instance, that we want to predict aortaruptures from the acceleration level of the thorax and from the forces applied to the rib cage.
The model matrix might look as follows:

acceleration A	force F
P(I/A)	P(I/F)
P(II/A)	P(II/F)

level I: aorta rupture

level II: no aorta rupture

In which:

P(I/A) denotes: the probability of level I given acceleration A
P(II/A) " : the probability of level II given acceleration A (= 1-P(I/A))
P(I/F) " : the probability of level I given force F
P(II/F) " : the probability of level I given force F(= 1-P(I/F))

If we may assume that acceleration A and force F may act independently then the total probability of level I and II can be calculated by:

$$P(I/A,F) = P(I/A) + P(I/F) - P(I/A) * P(I/F)$$

and, since I and II are mutually exclusive:

$$P(II/A,F) = 1 - P(I/A,F)$$

Apart from levels of force and acceleration, there may be a number of personal characteristics that play a role in the calculation of probability levels.
Moreover, instead of two injury levels we may need an arbitrary number of levels.

If we generalise the above calculation for injury levels as well as influential factors it can be shown that:

$$P(k/a_1, a_2 \ldots a_r) = \sum_{i=2}^{r} \left\{ P(k/a_{i-1}) + P(k/a_i) - P(k/a_i) \times \sum_{j=1}^{s-1} P(j/a_{i-1}) \right\}$$

where: r denotes the number of influential factors

s denotes the number of injury levels

$P(k/a_i)$ denotes the probability of injury level k, given the evidence of factor a_i.

The calculations as shown above are only possible if we have some means of obtaining the values $P(k/a_i)$.
These values must be derived from the literature and research data. To this end, a substantial number of statistical methods can be utilised, all depending on the nature of the data so it is not meaningful to choose any such method as yet.
Generally speaking the data processing to derive the probability $P(k/a_i)$ consists of three stages:

- stage 1: collection and preselection of influential variables
- stage 2: selection of those variables that are most significant to the prediction of a certain injury; this is the most complicated operation, which probably needs a non-linear correlation technique
- stage 3: calculation of the probabilities pertaining to the selected variables simply by counting of cases in each category.

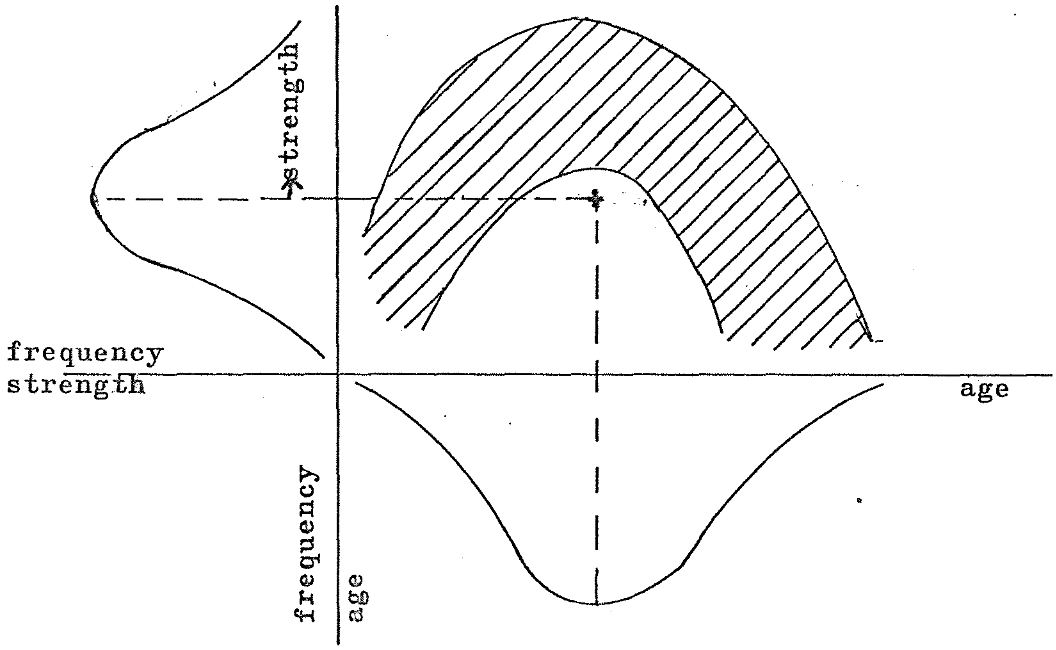
Appendix B

Simultaneous distributions

In problêms as the current one, in which a great number of parameters must be taken into account, we must consider the possible inter-dependence of certain of those parameters.

This is especially important if we want to make selections (samples) from the collected parameter data since the inter-dependence prohibits independent selection.
To illustrate that effect we will consider a simple example of two parameters that are non-linearly correlated.

Say, that in a survey of cadaver data, we have established that the relation between age and breaking strength of tibia bone may be represented by the following diagram (all data points fit within the drawn band).



Also plotted along the axis, are the frequency distributions of the variables.

Let us assume that both are normal distributions (it is an example, not based on real data).
Now, if we would treat the variables independently we could take the 50 percentile value for both parameters and declare that pair of parameter values as one of our selections, as a typical combination of values. However, as illustrated in the figure, the point corresponding to those values lies well outside the band; in this way we have selected parameters for a non-existent specimen.

Though this example by itself might not be a realistic one, it illustrates clearly that neglection of possible interdependence of variables may lead to unrealistic selections.

If we realise also that more than two variables of the total set of human data will probably be somehow related,we must take the consequence that we can treat none of those varibales as independent ones from the onset.

In the example, this means that, instead of using the frequency distributions along the axis, we must assing a frequency to each of the datapoints within the band, thus forming a 3-dimensional frequency-distribution function.
We may then proceed by dividing the band in a voluntary number of parts and find the average values for the parameters (age and strength) and the frequency corresponding to each part.

In practice, the consequences are more complex, because we must find a way to describe a multidimensional surface.
To that end we may employ techniques like multi dimensional curve fitting, linear- or non-linear interpolation between datapoints etc.
As for now, the exact method to be used is yet undecided, since this also depends straingly upon the nature of the data from literature.