

6 Fuzzy Decision Making in Public Health Strategies

Making decision is one of the most fundamental activities of human beings (Klir & Yuan, 1995; Yager & Filev, 1994; Zadeh, 1973). This is particularly true in Public Health where decisions usually have relevance for millions of people. In the field of vaccination strategies design, decision making concerning the target population for the immunization program, the proportion of susceptibles to be vaccinated, the optimal age to immunize children and the nature of the strategy, e.g. selective or indiscriminate, are examples of the variables to be optimized, subject to a set of constraints. As an example, we present in this chapter a fuzzy model to decision making applied to the design of the vaccination campaign against measles in São Paulo, Brazil (Massad *et al.*, 1999)

Decision making comprises the study of how decisions are actually made and how they can be made better or more successfully (Klir & Yuan, 1995). Models of human decision making generally include the aggregation criteria or criteria of constraints (Zimmermann, 1996). For the case that criteria and/or constraints cannot be modeled crisply but as fuzzy sets a decision has been defined by Bellman and Zadeh (1970) as the intersection of fuzzy sets representing either objectives or constraints. The grade of membership of an object in the intersection of two fuzzy sets, that is, the “fuzzy set decision” was determined by the use of both the *min* operator or the *product* operator (Zimmermann, 1996).

While decision making under conditions of risk have been modeled by probabilistic decision theories and game theories, fuzzy decision theories attempt to deal with vagueness and monospecificity inherent in human formulation of preferences, constraints, and goals (Klir & Yuan, 1995).

In the first paper on fuzzy decision making Bellman and Zadeh (1970) suggest a fuzzy model of decision making in which relevant goals and constraints are expressed in terms of fuzzy sets, and a decision is determined by an appropriate aggregation of these fuzzy sets. The decision models have the following components (Klir & Yuan, 1995):

- a set A of *possible actions*;
- a set of *goals*, $G_i (i \in \mathbf{N})$, each of which is expressed in terms of a fuzzy set defined on A ;

- a set of *constraints*, $C_j (j \in \mathbf{M})$, each of which is also expressed in terms of a fuzzy set defined on A .

The fuzzy set of decision, D , is that which simultaneously satisfies the given goals G_i and constraints C_j , and is:

$$D(a) = \min \left[\inf_{i \in \mathbf{N}} G_i(a), \inf_{j \in \mathbf{M}} C_j(a) \right] \quad (6.1)$$

for all $a \in A$.

6.1 Designing a Vaccination Strategy

Let us assume that the objective of a vaccination campaign is the reduction of the incidence of an infection like measles in children below 14 years of age, the age interval where viral infections are most likely to be circulating. This assumption is based on previous works which demonstrated that the force of infection of the measles virus has a strong age-dependence, peaking around 2 years of age in the absence of vaccination (Anderson & May, 1991). Therefore, in spite of the high proportion of cases in the age interval between 20 and 39 years of age, the highest incidence rate (normalized per 100,000 inhabitants) observed during the epidemic occurred in children below 5 years old. In addition, contact patterns suggest that adult cases are the product of infective contacts of susceptible individuals in that age interval with children below 14 years old (Massad *et al.*, 1994b), the target age interval of the vaccination campaign. All the subsequent analysis in this work are based on the assumptions above.

We begin by considering 8 possible vaccination strategies, composed by combinations of *Selective* vaccination, S_i , meaning vaccinating only children without vaccination record in the past, and *Indiscriminate* vaccination, I_j , that is, vaccinating children irrespective of previous immunization history (i and j stands for the age intervals). Besides, we considered the use of *Mobile Units*, $M.U.$, meaning those vaccination sites that are not part of the Primary Care Network, as opposed to *Fixed Units*, $F.U.$, those belonging to the network. Table 6.1 shows the various vaccination strategies considered.

The number of children, as well as the estimated proportion and number of susceptible children (assuming the seroepidemiological profile of 1994 and the drop in the routine measles vaccine coverage discussed above) in each age interval of São Paulo State is shown in table 6.2.

The last column of table 6.2 is the maximum theoretical number of children to be vaccinated in each age interval in order to stop the progression of the current epidemics. The optimal strategy, therefore, would be that which would maximize the number of susceptible children vaccinated in the target age interval, without wasting resources by over-vaccinating children in any specific age interval.

The next step was to invite a number of experts from the Health Secretary of São Paulo with great experience in vaccination campaigns in order to provide a

Table 6.1. Possible vaccination strategies (modified from Massad *et al.*, 1999)

Strategy	Age intervals and immunization history	Units Type
1	S_{9m-6y} and I_{6y-14y}	M.U.+F.U.
2	S_{9m-6y} and I_{6y-14y}	F.U.
3	S_{9m-14y}	M.U.+F.U.
4	S_{6y-14y} and I_{9m-6y}	M.U.+F.U.
5	I_{9m-14y}	M.U.+F.U.
6	S_{9m-6y}	F.U.
7	S_{9m-6y}	M.U.+F.U.
8	I_{9m-6y}	M.U.+F.U.

Table 6.2. Number, proportion of susceptible and number of susceptible children in the target age-interval (modified from Massad *et al.*, 1999)

Age	Number of* children	Proportion of+ susceptible	Number of susceptible
9m	49,500	0.65	32,175
10m	49,500	0.50	24,750
11m	49,500	0.50	24,750
12m	49,500	0.50	24,750
1-2y	640,609	0.10	64,061
3-5y	2,515,711	0.05	125,786
6-14y	5,920,000	0.05	296,000
Total	9,274,331	-	592,272

* Estimated from official data.

+ Estimated by dynamical modeling (Massad *et al.*, 1994b).

scale of efficacy and/or constraints of each of the possible strategies considered. The variables chosen by this experts team were:

- *compliance* by the population, that is, the proportion of the target population expected to attend the campaign convocation of each possible strategy;
- *human resources*, a relative scale of the staff required (including the training) for the implementation of each possible strategy;
- *transportation*, a relative scale of the difficulties in transport of people and material of each possible strategy;
- *communication*, a relative scale of the difficulties in explain to the population each possible campaign.

The minimum value of each of the variables will be that which determine the success of the strategy. The result of such a consultation to the experts is presented in table 6.3.

Values provided by the experts can be considered either as a proportion of expected success of each strategy or as degrees of membership to the fuzzy sets of

Table 6.3. Variables determinants of strategy success (Massad *et al.*, 1999)

Strategy	Compliance	Human Resources	Transp.	Communic.	min
1	0.30	0.30	0.20	0.30	0.20
2	0.45	0.60	1.00	0.50	0.45
3	0.70	0.50	0.30	0.40	0.30
4	0.40	0.40	0.30	0.40	0.30
5	0.80	0.20	0.20	0.80	0.20
6	0.60	1.00	1.00	0.70	0.60
7	0.50	0.60	0.60	0.60	0.50
8	1.00	0.70	0.40	1.00	0.40

successful strategies. In both views the *min* operator is the one which determine the expected results of each strategy. In addition, the *max* operator could be applied in this stage of the analysis if we consider the variables presented in table 6.3 as the only constraint of the strategies. According to this method, the strategy which maximizes the success of the campaign would be the strategy number 6.

The *min* values of the variables presented in table 6.3 allowed us to estimated the expected number of children, in each age class, that would be vaccinated in each of the possible strategies. So, for instance, strategy number one has as limitation the transport of people and materials and would, therefore, cover only 20% of the target population. As that strategy proposed to vaccinate children selectively from 9 months to 6 years of age and indiscriminately from 6 to 14 years of age, only 20% of the susceptibles below 6 years and 20% of all children from 6 to 14 years old would receive the vaccine. The minimum square of the difference between the number of children desired to receive the vaccine and the number of children that the strategy would actually vaccinate in each age class should determine the efficacy of each possible strategy, according to the definition of optimal strategy, as presented above.

A normalized scale of the efficacy of each strategy is shown in table 6.4. This was obtained by assuming that the most efficacious strategy is the one with the minimum square difference, assigned value 1. The others are obtained as a relative scale basing on multiples of the minimum square difference. Table 6.4 shows also the result of the economic costs of each strategy. This was calculated assuming a unit cost of US\$0.25 for the single measles vaccine, US\$1.40 for the measles-mumps-rubella (MMR) vaccine (applied only in children older than one year of age) and a unit cost of US\$0.75 for the application of the vaccines. So, the economic cost of each strategy is obtained by the sum of the vaccine and application unit costs times the total number of doses of each vaccine used (measles and MMR).

The next step in the analysis is to compare the two constraints to the success of each strategy, namely, those relative to the technical constraints (*adhesion, human resources, transportation and communication*) and those relative to costs.

Table 6.4. A comparative scale of relative efficacies and economic costs for each strategy (Massad *et al.*, 1999)

Strategy	Number of vaccinated	Relative efficacy	Economic costs (US\$)	Relative costs
1	1,243,254	0.049	3,178,223	0.533
2	2,797,322	0.098	5,959,168	1.000
3	177,682	1.000	414,359	0.070
4	1,095,099	0.127	2,743,384	0.460
5	1,854,866	0.045	4,730,907	0.794
6	177,763	0.770	308,758	0.052
7	148,136	0.761	370,509	0.062
8	1,341,732	0.147	3,352,374	0.563

Table 6.5. Degree of memberships of technical and costs constraints for each strategy (Massad *et al.*, 1999)

Strategy	Technical constraints	Costs [#] constraints	min
1	0.20	0.467	0.20
2	0.45	0.000	0.00
3	0.30	0.930	0.30
4	0.30	0.540	0.30
5	0.20	0.206	0.20
6	0.60	0.948	0.60
7	0.50	0.938	0.50
8	0.40	0.437	0.40

[#] Complement of column 5 (*Relative costs*) of table 6.4.

For this we took the minimum between the minimum of the variables presented by the experts (last column of table 6.3) and the complement to the relative costs scale (1-relative cost), so that both scales are in the same constraint direction, such that their minimum values represent the maximum constraint, as shown in table 6.5:

Now we have all the components of the decision model:

- a set A of *possible actions*: the eight possible strategies;
- a set of *goals*, G_i ($i \in \mathbf{N}$) defined on A : the relative efficacy of each possible strategy (third column of table 6.4) ¹; and
- a set of *constraints* C_j ($j \in \mathbf{M}$), defined on A : the minimum between the technical and costs constraints (last column of table 6.5).

¹ Remarking that by “goal” (this is the jargon in fuzzy optimal control theory) we mean the achievable efficacy of each possible strategy and not the major goal of controlling the epidemic.

Table 6.6. Fuzzy decision setting (Massad *et al.*, 1999)

Strategy	$G_i(a)$	$C_j(a)$	$D(a)$
1	0.049	0.200	0.049
2	0.098	0.000	0.000
3	1.000	0.300	0.300
4	0.127	0.300	0.127
5	0.045	0.200	0.045
6	0.770	0.600	0.600
7	0.761	0.500	0.500
8	0.147	0.400	0.147

The fuzzy decision, D , that simultaneously satisfies the given goals G_i and constraints C_j , is then:

$$D(a) = \min [G_i(a), C_j(a)] \tag{6.2}$$

for all $a \in A$, that is:

Therefore, the strategy that has the maximum degree of membership in the set of decision is strategy number 6, which selectively vaccinate children aged from 9 months to 6 years, using only Fixed Units of the health system. This strategy was then recommended to São Paulo public health authorities.

6.2 The Measles Epidemic in São Paulo

In São Paulo State, routine measles vaccination started in 1973. In spite of this, recurrent epidemics continue to occur until 1987, when the first mass vaccination campaign against measles was carried out, lessening the average incidence rate to something around 0.1 per 100,000 inhabitants.

By the end of September, 1996, the number of measles cases notified to São Paulo health authorities started to raise, interrupting a stability verified since the last major epidemic, in 1987. After March, 1997, the number of new cases started an exponential trend, characterizing the beginning of a new epidemic, which reached a total of 23,915 confirmed cases after one year, with 23 deaths. Regarding the age profile of the epidemic, it is noteworthy that 47% of the cases occurred in young adults, aged 20-29 years. The second age interval in number of cases, 15%, was that of children below one year old. However, the highest incidence rate, normalized per 100,000 inhabitants occurred among that latter age class. In what follows we briefly describe this episode, presented in details by Massad *et al.* (1999).

Table 6.7 describes the age profile of the epidemic, expressed as annual incidence rates, normalized by 100,000 inhabitants:

As can be seen from table 6.7, the highest incidence rates occurred in infants below one year of age, seconded by young adults in the age interval which corresponds to the expected age adults have greatest contact with young children.

Table 6.7. Age-related incidence rates per 100,000 inhabitants (Massad et al., 1999)

Age (years)	São Paulo city	State countryside	Total
< 1	871.50	94.17	482.84
1-4	115.99	15.32	65.65
5-9	61.21	13.13	37.17
10-14	36.17	5.93	21.05
15-19	67.27	11.34	39.31
20-29	314.30	29.85	172.08
30-44	56.52	7.54	32.03

Those adults belong to the reproductive age stratus and probably represent the parents of the children under the highest attack rates.

Figure 6.1 shows the epidemic wave in São Paulo State (bold continuous line), in the interior of the State (broken line) and in the City of São Paulo (dashed line), during the year of 1997.

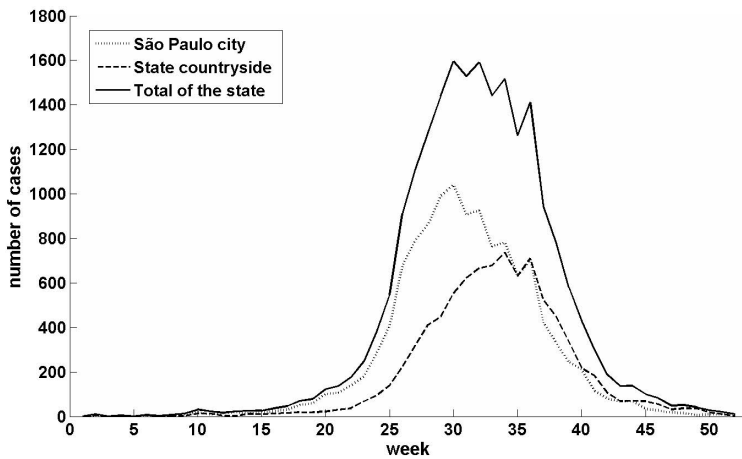


Fig. 6.1. Epidemic wave of measles in São Paulo, Brazil, in 1997. The two vertical dotted lines mark the moments of the two campaigns (Massad *et al.*, 1999).

6.3 The Impact of the Vaccination

Health impact assessment (HIA) is a developing approach that assesses the health impacts of a proposal on a population, and produces a practical set of recommendations to inform the decision-making process of the proposal. The purpose is to influence decision makers to increase positive health impacts of a proposal and decrease any identified negative impacts (Quigley & Taylor, 2004; Health Development Agency - UK, 2002). It is not an academic exercise. HIA

aims to provide a practical public health approach that can be used to address health concerns about a proposal and to reduce health inequalities (Department of Health - UK, 1999).

6.3.1 Forecasting and Projection Models

As mentioned in chapter 3, three major aims of mathematical models in epidemiology can be identified: the first centers on the need for scientific understanding and precision in the expression of current theories and concepts; a second aim, linked to the first, is the role of theory in identifying areas in which better epidemiological data is required to refine prediction and improve understanding; and the third, and in many instances, the most difficult objective is that of prediction (Anderson, 1988). In addition to these three aims of modeling we propose a fourth objective: the generation of testable hypotheses by providing a theoretical framework on which plausible scenarios can be simulated in a computer environment (in silicon experiments).

Prediction in general science can be divided into two components: forecasting and projections (Keyfitz, 1972). A forecast is an attempt to predict what will happen. A projection is an attempt to describe what would happen, given certain hypotheses (Caswell, 2000). Among the tools available to the modern epidemiologists for both forecasting and projection are the mathematical (or dynamical) models, which, when well structured, can provide predictive capacity to the public health professional, helping in the design, and assessment of the impact of control strategies (Amaku *et al.*, 2003; Burattini *et al.*, 1998; Massad *et al.*, 1995; Burattini *et al.*, 1993). For instance, by projecting what would happen with a given population if individuals were not vaccinated, it is possible to quantify the relative impact of a specific vaccination program.

In what follows we illustrate the application of a projective model do the Severe Acute Respiratory Syndrome (SARS), describe in details in Massad *et al.* (2005b).

Severe Acute Respiratory Syndrome (SARS) is a recently discovered infectious disease with high potential for transmission (WER, 2003), transmitted by droplet and direct contact and caused by a new strain of corona virus (CDC, 2003). On 5 July 2003, World Health Organization (WHO, 2003) announced that the last known chain of human-to-human transmission of the SARS corona virus had been broken. A cumulative number of 8422 cases have been reported worldwide to the WHO, with 908 deaths, as of August, 2003.

In the end of 2002, reports from China suggested that a new, highly contagious, and very severe atypical pneumonia of unknown cause was occurring in the Guangdong province. As it reached southeastern Asian countries, the condition appeared to be particularly prevalent among health care workers and their household members. In response to that threat, on March 13, 2003, WHO issued a global alert, for the first time on more than a decade, and instituted worldwide surveillance. On March 27, scientists in the WHO laboratory network reported major progress in the identification of the causative agent, a new member of the corona virus family.

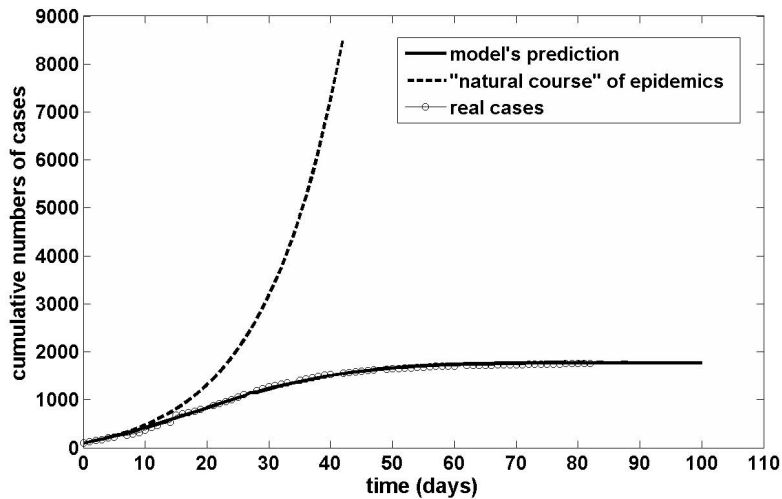


Fig. 6.2. The number of SARS real cases in Hong Kong, the model prediction and the natural course of the epidemics (Massad *et al.*, 2005b)

By that time, SARS has already become a global health hazard, and its high infectivity was alarming. Early recognition, prompt isolation, and appropriate precaution measures were considered to be key factors in combating this infection (Lee *et al.*, 2003). In figure 6.2 we show the simulation for the Hong Kong community.

The model mimics real data with good accuracy when considering adoption of control measures. The model's prediction demonstrated an epidemic that is, by far, milder than expected without control measures. The model projects that, in the absence of control, the final number of cases would be 320,000 in Hong Kong. In contrast, with control measures, which reduce the contact rate to about 25% of its initial value, the expected final number of cases is reduced to 1,778. In fact, the stability level predicted by the model was indeed attained in Hong Kong by the end of the outbreaks.

6.3.2 The Case of the Measles Epidemic in São Paulo

In June 21, 1997, the proposed vaccination strategy was implemented in the State of São Paulo. A total of 213,084 doses were applied to children between 9 months and 6 years of age. This figures represents a coverage of 6.5% of the entire population of the State of São Paulo in the target age interval. In the Metropolitan Region of São Paulo city, 7.5% of the entire population in the target age interval was vaccinated. In the interior of the State 5.1% of the population in the target age interval was vaccinated. There are no official data on the efficacy of the selection process, that is, it is not known whether the small proportion of children vaccinated were those previously unvaccinated or not.

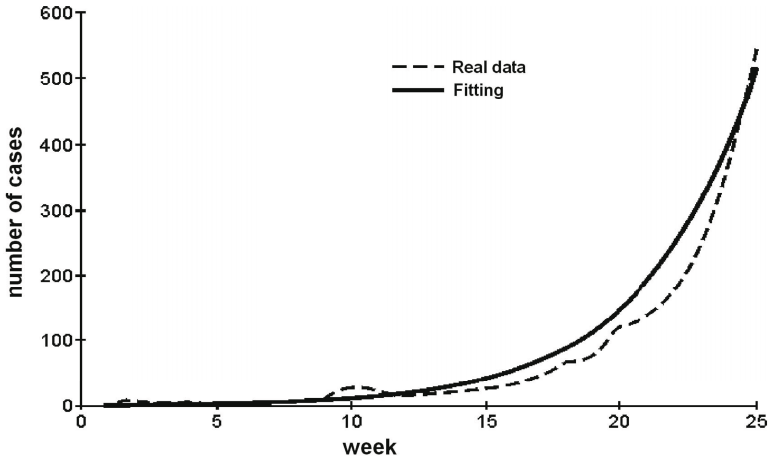


Fig. 6.3. Fitting of the continuous function to the initial phase of the actual epidemic until the last week before the first intervention (Massad *et al.*, 1999)

In order to estimate what would be the natural course of the epidemic we first fitted a continuous function to the initial phase of the actual epidemic until the last week before the first intervention. As expected, it resulted in an exponential curve, with a positive growing rate of 0.25/week. Figure 6.3 shows the result of this fitting.

Next, we calculated the effective contact rate, β , a composite rate describing the probability of contact between susceptible and infected individuals and the probability that such a contact will result in a new case. This was done by assuming that the number of new infections, $y(t)$, increase exponentially as seen in figure 6.3, according to:

$$y(t) = y(0) \exp\{[\beta \bar{x} - (\mu + \gamma)]t\} \tag{6.3}$$

where \bar{x} is the expected proportion of susceptibles, assumed to be equal to 10%; μ is the natural mortality rate of the population, assumed to be equal to 0.0003/week and γ is the inverse of the infectiousness period of measles, assumed to be equal to 1 week. The term between square brackets resulted in a value of β equal to 12.5/week.

Those parameters then fed a dynamical system of the classical SIR type, in order to retrieve the natural course of the epidemic in the absence of vaccination. The model had the form:

$$\begin{aligned} \frac{dx(t)}{dt} &= \mu[y(t) + z(t)] - \beta x(t)y(t) \\ \frac{dy(t)}{dt} &= \beta x(t)y(t) - (\mu + \gamma)y(t) \\ \frac{dz(t)}{dt} &= \gamma y(t) - \mu z(t) \end{aligned} \tag{6.4}$$

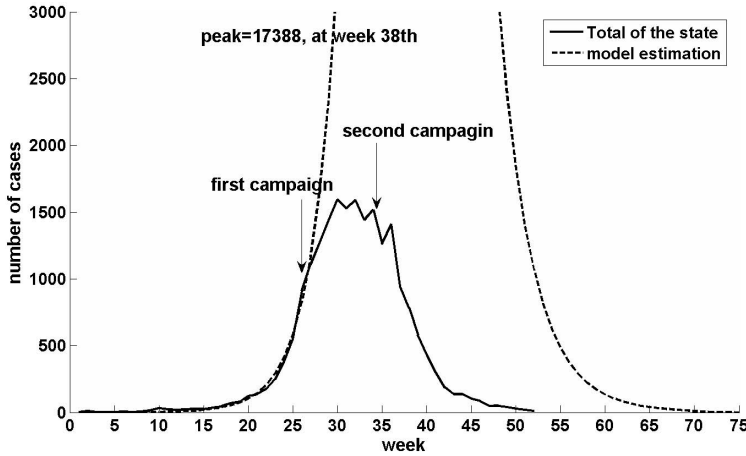


Fig. 6.4. The results of the model simulation and the actual epidemic underlying (Massad *et al.*, 1999)

where $z(t)$ represents the recovered (immune) individuals. The result of the simulation, with initial conditions $x(0) = 0.1$; $y(0) = 10^{-7}$ and $z(0) \cong 0.9$, with the actual epidemic underlying, can be seen in figure 6.4.

As can be noted from figure 6.4, the expected number of cases simulated by the model above would peak at around 17,500 cases at the 38th week, totalizing almost 300,000 cases. This would represent an attack rate of around 8% of the susceptible population, a figure which is in the lower bound of others measles epidemic reported in the literature (Markowitz & Katz, 1994; Hutchins *et al.*, 1990; Weeks *et al.*, 1992). Also noteworthy in figure 6.4 is the striking concordance between the simulated curve and the actual epidemic until week 25. In this point, there is a significant deflection of the exponential trend of the epidemic curve, which occurred just after the first intervention.

By comparing the expected (simulated) number of cases with that seen in the actual epidemic we may conclude that the proposed vaccination strategy (carried out at week 25) had a significant impact on the epidemic in the city of São Paulo. However, as can be seen from figure 6.1, the number of cases in the interior of the State continued to raise after the first campaign, peaking around ten weeks after. Possible causes for this shall be discussed later on. Health authorities then decided to carry out a second campaign which differed from the first one by the virtual absence of costs constraints considerations. Strategy number eight, therefore, was the best choice available, because it has the highest adhesion, and it was implemented in August 16 (which corresponds to week 33). The total number of cases dropped significantly in all age strata and in the whole State soon after the second vaccination and the epidemic was then considered controlled.

In spite of a 95% efficient vaccine available for more than 25 years, measles still remains an important public health problem, killing every year more than one

million children in the developing regions (Murray & Lopez, 1996) and with a *Disability-Adjusted Life Years* (DALY) measure of 36.5×10^6 , which is even higher than malaria (31.7×10^6) for the same regions (Murray & Lopez, 1996). As a very transmissible infection with a Basic Reproduction Number (Anderson & May, 1991) usually above 15, it demands very high levels of vaccine coverage (above 93%) in order to be eliminated. However, these levels of coverage are rarely maintained in the routine schemes of immunization. Therefore, it is an usual control strategy, at least in developing countries, to carry out mass vaccination campaigns from time to time. In fact, this occurred in the State of São Paulo in 1987 and again in 1992, with a significant impact on measles incidence.

It is common to observe a severe dropping of cases shortly after a mass vaccination campaign. As time passes by, however, the residual fraction of non-responders to the vaccine and the immigration of susceptible individuals from other areas of the country, starts to accumulate in the population. This fact allied to the marked dropping in the coverage levels in the immunization routine observed in the last two years in the State of São Paulo, may explain the 1997 epidemic.

A subject of hot debate among public health authors, periodic mass vaccination has been considered an effective way to control measles epidemics (Nokes & Swinton, 1997). The design of such a vaccination strategy is based on the rate of replenishment of susceptibles into the population that follows the vaccination. In the case when the mass vaccination is intended to supplement an existing routine (the case of São Paulo State), the rationale is as follows (Nokes & Swinton, 1997): the replenishment of susceptibles equal the birth rate, $1/L$ (as in other works, L denotes the population life expectancy), reduced by a fraction $(1-p)$, where p is the proportion of newborn effectively vaccinated in the routine schedule. If we denote the proportion of children vaccinated in the campaign as p' , then the interval, T_v , between two successive campaigns is given by:

$$T_v = \frac{p'A}{(1-p)}, \quad (6.5)$$

where A is the average age of the first infection.

In very populous countries like Brazil and, in particular, in regions like the State of São Paulo, where mass vaccination campaigns are aimed to cover millions of individuals, any reasonable estimate of the minimum number to be vaccinated could represent savings of millions of dollars to public money.

When the São Paulo epidemic was detected and the vaccination campaign decided, very few data was available to allow the application of dynamical modeling, a more structured approach, to the design of the optimal vaccination schedule (Massad *et al.*, 1994b). Moreover, the dynamics of a measles epidemic shortly after an intervention such as a mass vaccination campaign has been poorly documented in the literature. So, it would be very difficult to predict the impact of the intervention on the course of the epidemic. In addition, an important constraint was imposed - the total number of doses available was dangerously limited to 300,000. This scenario encouraged us to attempt, for the

first time (to the best of our knowledge), the use of fuzzy logic concepts to design the vaccination campaign.

The capacity of the fuzzy decision model in predicting the number of children that could be reached by the vaccination strategy can be evaluated by contrasting this number (177,763, which corresponds to 60% of the susceptibles in the targeted population) with the actual number of children who received the vaccine (213,084, which corresponds to 72% of the susceptibles in the targeted population). Therefore, the fuzzy model prediction of the number of children that should be vaccinated has an accuracy of more than 80%. As a result the efficacy of the strategy was significant, at least for the metropolitan region of São Paulo city (figure 6.4), notwithstanding the minor impact seen in the rest of the State. A possible explanation for this could be a lack of adequacy of the selectiveness criteria adopted (to vaccinate only previously unvaccinated children). As a matter of fact, another uncertainty, not forecasted by the initial model, was the decision of public health authorities to extend the measles campaign to a broader scope strategy that included other vaccines like diphtheria-pertussis-tetanus (DPT). However, shortly after midday of June, 21, the DPT vaccine run out of stock, which probably demobilized the population. The latter argument is intended only as an example of how unexpected facts can influence the final result of such a complex endeavor like a mass vaccination campaign. In conclusion, we think that the fuzzy logic approach for designing the control strategy against the measles epidemic in São Paulo was very useful in the sense that it allowed the combination of intuitive informations from public health experts and costs constraints into a coherent model. Moreover it proved to be very effective, in the sense that the strategy adopted resulted in a significant control of the epidemic. Our results, notwithstanding several intervenient factors out of our control during the implementation of the proposed strategy, are very encouraging in demonstrating the potential of new techniques for the designing of interventions in public health.

Maybe the great advantage of the making decision approach proposed by Bellman and Zadeh applied here is its simplicity, both from the practical and theoretical points of view (Bellman & Zadeh, 1970). This simplicity allowed that the fuzzy model for design a control strategy for vaccination against measles could be developed quickly. In fact, this model was elaborated, in a consensus form, in just two meetings. At the final of the second meeting the best strategy elected by the model was accepted by all experts and in few days it was implemented in whole São Paulo State. Clearly, from the sanitary surveillance point of view, the agility and the adhesion capacity are important characteristics desired in the mathematical models.

Stochastic Decision Trees is one of the most traditional approach to decision making that deals with uncertainty in health care applications (Mason *et al.*, 1995; Col *et al.*, 1997; Onho-Machado *et al.*, 2000). In order to compare the fuzzy decision making with other more traditional probabilistic methods, Onho-Machado and collaborators (2000) studied the same situation with the decision trees technique. The authors built a ranking of the strategies to control

the measles epidemic in 1997, in Brazil, considering the same structure proposed in the fuzzy decision making and compared them (Onho-Machado *et al.*, 2000). The models identify the same strategy as being the best one, but exhibit differences in the ranking starting from the fourth strategy. So, in terms of the health care decision making the fuzzy model and the stochastic decision trees were completely equivalent. Thus, the differences between the two approaches refer only to the mathematical structures and, in this case, the fuzzy decision approach presents the advantage of its mathematical simplicity, which resulted in a great adhesion power.