MODIFIED MULTIPLE DECREMENT TABLE AND ITS CREDIBILITY BASED ON FACTOR CHARACTERISTICS

RANDI DEAUTAMA¹, KURNIA NOVITA SARI²

¹Master Program in Actuarial Science, Faculty of Mathematics and Natural Sciences, Institut Teknologi Bandung, rnddea@gmail.com
 ²Statistics Research Division, Faculty of Mathematics and Natural Sciences, Institut Teknologi Bandung, kurnia@math.itb.ac.id

Abstract. The 2019 Indonesian Mortality Table IV (TMI IV) involved 52 life insurance companies in Indonesia during the study period from 2013 to 2017. From the data, there may be differences in the characteristics of company customers so that the use of TMI IV is not in accordance with these characteristics. In life insurance companies, there are types of coverage (causes), namely: NDPA, which means death due to illness or accident; PAD, which means reimbursement of medical expenses; and SRD, which is the cancellation of the policy so that the coverage ends. The Companies can construct a Life Table involving multiple causes called a Multiple Decrement (MD) Table. This table is modified into a Modified Multiple Decrement Table (MDT) by adding factors to the causes in the form of regions. The clustering of factors needs to be done to reduce the complexity of the calculation. Using the K-means method, the grouping of regions R1R9 is divided into the following: PAD causes (3 groups) and SRD (2 groups). MDT is obtained from the relationship between MD and the Associated Single Decrement (ASD). The Annual Exposure Method was used to calculate the probability of causes. Furthermore, extrapolation is performed on the probability of cause, for which there is no value, and graduation is performed on the less smooth probability of cause. Then, credibility theory is used to determine the credibility level of the industry. The industry-credible probability of cause has a value between the observed value and the industry value (TMI IV).

 $Key\ words\ and\ Phrases:$ associated single decrement, clustering, extrapolation and graduation, credibility theory, modified multiple decrement

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1. INTRODUCTION

In the preparation of TMI IV, 52 life insurance companies in Indonesia were involved in the study period from 2013 to 2017. The data provided by the 52 life insurance companies may represent the data of each life insurance company. However, it is possible that there are differences in the distribution of insurance agents in each life insurance company, which means that there are also differences in the characteristics of life insurance participants, so that the data is feared to be less representative of the data of all life insurance companies. Therefore, every life insurance company in Indonesia is expected to have a mortality table that describes the characteristics of the life insurance company participants by considering TMI IV.

In life insurance companies, there are several types of coverage that are commonly used, namely NDPA, which means death due to illness or accident; PAD, which means reimbursement of medical expenses; and SRD means surrender which participants who withdraw from the policy. These types of coverage are referred to as causes that cause the end of coverage, and the insurance company must pay a sum of money or, specifically, for withdrawal, the company must return the remaining premium paid by the participant in accordance with the agreed-upon agreement.

Based on the above conditions, life insurance companies can construct a modified mortality table with various causes, or the so-called Multiple Decrement Table. This model builds a distribution between two random variables applied to one life, namely the remaining time until a person leaves the system [1], [2] used the Kendall Model to construct the Multiple Increment-Decrement Table of the HIV population, [3] modified the Multiple Decrement Model based on the conditions of various diseases in Northern Ghana, [4] used Markov chains to calculate the worst condition in multiple decrement, and [5] built multiple decrement using an associated single decrement assuming constant and linear acceleration as well as [6] constructed the multiple decrement table using the fractional age assumption expansion method. As of [7] used markov model in a Multiple State Model for premium calculation when several premium-paid states are involved and [8] explored Hierarchical Markov Model in life insurance and social benefit schemes. Then, [9] applied a multiple decrement life table model for orphan daughters in Turkey and [10] contruct decrement rates and a numerical method under competing risks.

In this study, the Multiple Decrement Model (MDM) will be modified by including a factor for each cause. This factor can be a region or another factor. Each cause can have the same or different factors, depending on the selection of factors that have a significant influence on the cause. This model is referred to as the Modified Multiple Decrement Model (MMDM). The Associated Single Decrement Model is used directly to obtain the multiple decrement probability. The cause probability (associated single decrement) is calculated using the annual exposure method for each cause per factor. Here is the MMDM and how it differs from the MDM.

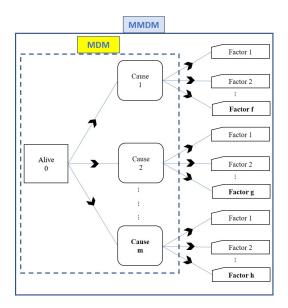


FIGURE 1. Modified multiple decrement model (non-dashed line) and multiple decrement model (dashes line)

The cause factors should be grouped under the same type of risk. This is done to streamline computation, thus saving research time and cost as well as allowing for clear risk segmentation. Since the company experience data is not as extensive as the industry data, there may be empty cause probability, so extrapolation and graduation are used to obtain smooth cause probability. Furthermore, credibility theory is used to obtain credible cause probability for the industry (TMI IV), especially for death probability.

2. MODIFIED MULTIPLE DECREMENT MODEL

In Figure 1, the Modified Multiple Decrement Model is an extension of the Multiple Decrement Model, namely by adding factors to each cause. In Chapter 2.1 and 2.2, the Multiple Decrement Model, the Associated Single Decrement Model and their relationship will be explained. Next, the Multiple Decrement Model with Factors (Modified Multiple Decrement Model) will be elaborated.

2.1. Multiple Decrement Model (MD). Based on [11] let J be a discrete r.v. representing the cause of an individual (x), a person's age at x, leaving the system and T be a continuous r.v. representing the time until (x) leaves the system. The values of the two r.v's are,

$$T \geq 0$$
 and $J = 1, 2, \dots, m$.

The joint probability and marginal probability of T and J, respectively,

$$f_{T,J}(t,j) = {}_{t}p_{x}^{\tau}\mu_{x+t}^{j}$$
$$f_{T}(t) = {}_{t}p_{x}^{\tau}\mu_{x+t}^{\tau}$$
$$f_{J}(j) = {}_{\infty}q_{x}^{(j)}$$

as well as the total of distribution function, survival function, and hazard function, respectively,

$$tq_x^{(\tau)} = \sum_{j=1}^m tq_x^{(j)}$$
$$tp_x^{(\tau)} = 1 - tq_x^{(\tau)}$$
$$\mu_{x+t}^{(\tau)} = \sum_{j=1}^m \mu_{x+t}^{(j)}$$

2.2. Associated Single Decrement Model (ASD). There is a relationship between the MD Model and the ASD Model. The probability of (x) staying in the system due to all causes in (x, x + t],

$$_{t}p_{x}^{(\tau)} = \prod_{j=1}^{m} _{t}p_{x}^{'(j)} \tag{1}$$

Proof.

$$t p_x^{(\tau)} = \exp\left(-\int_0^t \mu_{x+s}^{(\tau)} ds\right) = \exp\left(-\int_0^t \sum_{j=1}^m \mu_{x+s}^{(j)} ds\right) = \prod_{j=1}^m \exp\left(-\int_0^t \mu_{x+s}^{(\tau)} ds\right)$$
$$= \prod_{j=1}^m t p_x^{'(j)}.$$

It is known that $_{t}p_{x}^{'(j)} \in (0,1)$. Then, $_{t}p_{x}^{(\tau)} \leq _{t}p_{x}^{'(j)} \in (0,1) \forall j$ so, $_{t}qx^{(\tau)} \geq _{t}qx^{'(j)}$, consequence, $q_{x}^{(j)} \leq q_{x}^{'(j)} \leq q_{x}^{(\tau)}$.

Proof.

$$\int_0^1 {}_t p_x^{'(j)} \mu_{x+t}^{(j)} dt = -\int_0^1 \frac{d}{dt} {}_t p_x^{'(j)} 1 dt = -\left({}_t p_x^{'(j)}\right)_0^1 + \int_0^1 {}_t p_x^{'(j)} \frac{d}{dt} 1 = 1 - p_x^{'(j)} = q_x^{'(j)}.$$

$$tp_{x}^{'(j)}\mu_{x+t}^{(j)} \ge tpx^{(\tau)}\mu_{x+t}^{(j)}$$

$$q_{x}^{'(j)} = \int_{0}^{1} tp_{x}^{'(j)}\mu_{x+t}^{(j)}dt \ge \int_{0}^{1} tpx^{(\tau)}\mu_{x+t}^{(j)}dt = q_{x}^{(j)}.$$

Based on Equation (1), it is obtained relation between $_tq_x^{(\tau)}$ and $_tq_x^{'(j)}$ as following,

$${}_{t}q_{x}^{(\tau)} = \sum_{n=1}^{m} (-1)^{n-1} {}_{t}N_{n} \tag{2}$$

where $_tN_n$ is sum of combination n $_tq_x^{'(j)}$ from all its possibilities. As example with m=3, $_tN_2=_tq_x^{'(1)}{}_tq_x^{'(2)}+_tq_x^{'(1)}{}_tq_x^{'(3)}+_tq_x^{'(2)}{}_tq_x^{'(3)}$.

Proof.

$$tq_x^{(\tau)} = 1 - \prod_{j=1}^m tp_x^{'(j)}$$

$$= 1 - tp_x^{'(1)} tp_x^{'(2)} \cdots tp_x^{'(m)}$$

$$= 1 - \left(1 - tq_x^{'(1)}\right) \left(1 - tq_x^{'(2)}\right) \cdots \left(1 - tq_x^{'(m)}\right)$$

$$= 1 - \left[1 + (-1)^1 tN_1 + (-1)^2 tN_2 + \cdots + (-1)^m tN_m\right]$$

$$= tN_1 + (-1)tN_2 + (-1)^2 tN_3 + \cdots + (-1)^{m-1} tN_m$$

Thus,

$$_{t}q_{x}^{(\tau)} = \sum_{n=1}^{m} (-1)^{n-1} {}_{t}N_{n}$$

Furthermore, from Equation (1) and (2) are obtained relation between $_tq_x^{(j)}$ and $_tq_x^{'(j)}$ which shows the direct relation between MD and ASD,

$${}_{t}q_{x}^{(j)} = {}_{t}q_{x}^{'(j)} \left[1 + \sum_{k=1}^{m-1} (-1)^{k} \left(\frac{1}{k+1} \right) {}_{t}C_{k} \right]$$
 (3)

where ${}_{t}C_{k}$ is a sum of combination $k {}_{t}q_{x}^{'(j)}$ from all its possibilities, except ${}_{t}q_{x}^{'(j)}$ corresponding with ${}_{t}q_{x}^{(j)}$. As example, let m=3 and j=2,

$$_{t}q_{x}^{(2)} = _{t}q_{x}^{'(2)} \left[1 + (-1)^{1} \left(\frac{1}{2} \right) _{t}C_{1} + (-1)^{2} \left(\frac{1}{3} \right) _{t}C_{2} \right]$$

where

$${}_{t}C_{1} = {}_{t}q_{x}^{'(1)} + {}_{t}q_{x}^{'(3)}$$
$${}_{t}C_{2} = {}_{t}q_{x}^{'(1)} {}_{t}q_{x}^{'(3)}.$$

2.3. Modified Multiple Decrement Model (MDT). Previously defined r.v J and T, respectively denote causes and time until termination of system. Let m = 3, with (j = 1) = D, (j = 2) = O, and (j = 3) = W. Define D_k denote cause D of

factor k, where k as much f; D_k where k as much g; W_k where k as much h. Based on Equation (1) is written,

$$_{t}p_{x}^{(\tau)}=_{t}p_{x}^{'(D)}_{t}p_{x}^{'(O)}_{t}p_{x}^{'(W)}\left(\prod_{k=1}^{f}{_{t}p_{x}^{(''D_{k})}}\right)\left(\prod_{k=1}^{g}{_{t}p_{x}^{(''O_{k})}}\right)\left(\prod_{k=1}^{h}{_{t}p_{x}^{(''W_{k})}}\right)$$

where $_{t}p_{x}^{(''D_{k})}$ is probability of cause D for factor k, that is without involve other factor and $_{t}p_{x}^{('D_{k})}$ involve other factor. Based on above equation is obtained,

$$_{t}q_{x}^{(\tau)} = \sum_{n=1}^{f+g+h} (-1)^{n-1} {}_{t}N_{n}.$$

As example with f = 2, g = 2, h = 2, get

$$\begin{split} tN_2 &= t q_x^{''(D_1)} t q_x^{''(D_2)} + t q_x^{''(D_1)} t q_x^{''(O_1)} + t q_x^{''(D_1)} t q_x^{''(O_2)} + t q_x^{''(D_1)} t q_x^{''(W_1)} \\ &+ t q_x^{''(D_1)} t q_x^{''(W_2)} + t q_x^{''(D_2)} t q_x^{''(O_1)} + t q_x^{''(D_2)} t q_x^{''(O_2)} + t q_x^{''(D_2)} t q_x^{''(W_1)} \\ &+ t q_x^{''(D_2)} t q_x^{''(W_2)} + t q_x^{''(O_1)} t q_x^{''(W_1)} + t q_x^{''(O_1)} t q_x^{''(W_2)} + t q_x^{''(O_2)} t q_x^{''(W_1)} \\ &+ t q_x^{''(O_2)} t q_x^{''(W_2)} + t q_x^{''(W_1)} t q_x^{''(W_2)}. \end{split}$$

Furthermore, from Equation (3) is obtained,

$${}_{t}q_{x}^{(j)} = {}_{t}q_{x}^{"(j)} \left[1 + \sum_{k=1}^{f+g+h-1} (-1)^{n} \left(\frac{1}{n+1} \right) {}_{t}C_{n} \right], \tag{4}$$

with same value of f, g, and h, as well as k = 2, for $(j = 1)_k = D_k$, get

$$_{t}q_{x}^{(D_{2})} = _{t}q_{x}^{"(D_{2})} \left[1 + \sum_{k=1}^{5} (-1)^{n} \left(\frac{1}{n+1} \right) _{t}C_{n} \right],$$

where ${}_{t}C_{n}$ is sum of combination $n {}_{t}q_{x}^{"(j_{k})}$ from 5 ${}_{t}q_{x}^{"(j_{k})}$ that ${}_{t}q_{x}^{"(D_{2})}$ corresponding with ${}_{t}q_{x}^{(D_{2})}$, exclude. Let for ${}_{t}C_{2}$,

$$tC_{2} = tq_{x}^{(''D_{1})}tq_{x}^{(''O_{1})} + tq_{x}^{(''D_{1})}tq_{x}^{(''W_{1})} + tq_{x}^{(''D_{1})}tq_{x}^{(''D_{1})}tq_{x}^{(''D_{1})} + tq_{x}^{(''D_{1})}tq_{x}^{(''W_{2})} + tq_{x}^{(''D_{1})}tq_{x}^{(''W_{1})} + tq_{x}^{(''O_{1})}tq_{x}^{(''W_{1})} + tq_{x}^{(''O_{2})}tq_{x}^{(''W_{1})} + tq_{x}^{(''O_{2})}tq_{x}^{(''W_{1})} + tq_{x}^{(''W_{1})}tq_{x}^{(''W_{1})}.$$

2.4. **Probability of Cause.** The cause probability is calculated per cause factor at each unit age, i.e., the number of cause events per factor at each age divided by the total exposure at each age, which is written as follows:

$$q_x^{"(j_k)} = \frac{d_x^{"(j_k)}}{E_-},\tag{5}$$

where $d_x^{"(j_k)}$ denotes the number of participants experiencing cause j_k in [x, x+1) and E_x is the number of years contributed up to age x. This exposure is calculated using the Seriatim Method.

2.5. Extrapolation, Graduation, and Credibility. The calculation result of $q_x^{"(j_k)}$ in Equation (4) still has empty values, so extrapolation and graduation are needed to get a smooth probability value. Extrapolation and graduation are only performed on the cause of death compared to TMI IV. Generally, extrapolation on mortality rates using the Gompertz-Makeham model is written as,

$$q_x''(D_k) = 1 - \exp\left[-\left(A + \frac{Bc^x(c-1)}{\ln c}\right)\right],$$
 (6)

with B > 0, $A \ge -B$, c > 1, and $x \ge 0$. After extrapolation, there are usually death rates that increase too much from the previous ages. Therefore, the mortality rate is graded to obtain a smooth mortality rate using the Whittaker-Henderson Method. This method minimizes a function of M which is written,

$$M = \sum_{x=1}^{n} w_x \left[q_x^{"(D_k)} - \left(q_x^{"(\hat{D}_k)} \right)^2 \right] + \lambda \sum_{x=1}^{n-d} \left(\Delta^d q_x^{"(\hat{D}_k)} \right). \tag{7}$$

The selection of smoothing parameter, λ , and degree of difference, d, uses crude search or grid search which is a numerical method.

The number of claims observed by a company is certainly less than the number of claims observed in the industry study (TMI IV). Therefore, credibility theory is needed to obtain a mortality rate that is weighted by the mortality rate in the industry study,

$$q_x^{"(D_k)} = Z \ q_x^{"(\hat{D}_k)} + (1 - Z) \ q_x^{TMI(IV)}.$$
 (8)

3. RESULTS

- 3.1. **Data.** The data used in this study is data from one life insurance company in Indonesia. The study period starts from 2010 to 2020 with 2153555 participants. These participants are spread over 9 (nine) regions, namely: $R1, R2, \cdots$, and R9. The causes observed are Natural/Personal Accident Death (NDPA), reimbursement of medical expenses (PAD), and surrender (SRD). Table contains the number of participants spread across the above 9 regions.
- 3.2. Construction of Multiple Decrement Table. The steps to construct the MD Table are as follows:
- 1. Use Equation (5) to calculate the probability of each cause per factor, $q_x^{''(j_k)}$, $j=NDPA, PAD, SRD, \, k=R1, R2, \cdots, R9$, and $x=17,18,\cdots,74$, 2. Fitting $q_x^{''(NDPA)_k}$ using the Gompertz-Makeham Distribution and graduating
- 2. Fitting $q_x^{(NDPA)_k}$ using the Gompertz-Makeham Distribution and graduating as well as applying the credibility of $\forall_{(NDPA_k)}$ using Equations (6), (7), and (8), respectively. Meanwhile, PAD and SRD cause according to the existing results,
- 3. Form clusters for the probability of a particular cause per factor using k-means clustering so that some new f, g, and h are obtained.

983,918

2,827

831

3,682

254,700

R1 R3Number of Number of Occurrences Number of Number of Occurrences Number of Number of Occurrences Age PAD Participants PAD PAD Participants NDPA SRD NDPA SRD Total Participants NDPA SRD Total Total 17-22 34,097 8,466 4,542 10 23-28 29-34 35-39 29,735 40,457 47,522 63 73 281 73 213 349 86,063 112,383 11,869 17,866 85 186 155 165 30 103 179 246 1,414 19,481 104,981 351 1,133 40-45 46-51 52-57 474 771 791 233 456 634 89 115 173 396.880 331 142 47.937 1.908 19.357 266 360 130 141,228 82,711 42,053 28,751 15,677 9,810 231 155 347 330 641 1,571 2,027 $\frac{728}{357}$ 1,420 59-63 150 20.718 444 8.328 295 445 5.701 229 230 459 4,071 786 1,169 282 151 45 1,636 529 143 36 64-69 299 30 32 183 215 358

Table 1. Data of region participants R1 - R9

| | | | R4 | | | | | R6 | | | | | | | |
|---------|--------------|-----------------------|-----|-------|--------|--------------|-------|---------|------------|-------|--------------|-----------------------|-----|-------|-------|
| Age | Number of | Number of Occurrences | | | | Number of | Nı | ımber o | f Occurren | ces | Number of | Number of Occurrences | | | |
| | Participants | NDPA | PAD | SRD | Total | Participants | NDPA | PAD | SRD | Total | Participants | NDPA | PAD | SRD | Total |
| 17-22 | 8,510 | 6 | | 39 | 45 | 7,816 | 20 | 20 | 7 | 47 | 13,020 | 11 | 6 | 6 | 23 |
| 23-28 | 32,451 | 31 | 1 | 443 | 475 | 8,867 | 19 | 7 | 102 | 128 | 5,058 | 6 | 1 | 94 | 101 |
| 29-34 | 50,663 | 75 | | 1,029 | 1,104 | 16,698 | 20 | 2 | 314 | 336 | 9,009 | 18 | | 307 | 325 |
| 35-39 | 58,442 | 370 | | 1,490 | 1,860 | 20,932 | 185 | | 540 | 725 | 11,539 | 113 | | 411 | 524 |
| 40-45 | 59,477 | 277 | | 1,695 | 1,972 | 24,281 | 111 | | 438 | 549 | 10,675 | 108 | | 348 | 456 |
| 46-51 | 52,699 | 532 | | 1,539 | 2,071 | 16,999 | 187 | 1 | 482 | 670 | 8,775 | 106 | | 279 | 385 |
| 52-57 | 33,286 | 666 | | 1,036 | 1,702 | 12,833 | 314 | 1 | 461 | 776 | 5,950 | 145 | | 121 | 266 |
| 59-63 | 13,646 | 589 | | 648 | 1,237 | 9,632 | 557 | | 612 | 1,169 | 6,758 | 434 | 1 | 472 | 907 |
| 64-69 | 2,235 | 352 | | 105 | 457 | 2,667 | 421 | 1 | 233 | 655 | 2,297 | 393 | | 129 | 522 |
| 70 - 74 | 453 | 153 | | 29 | 182 | 399 | 141 | | 20 | 161 | 354 | 205 | | 16 | 221 |
| Total | 311.862 | 3.051 | 1 | 8.053 | 11,105 | 121,124 | 1.975 | 32 | 3,209 | 5.216 | 73,435 | 1,539 | 8 | 2,183 | 3,730 |

2,240

7,771

10,014

106,468

1,120

| | | | R7 | | | | | R9 | | | | | | | |
|-------|--------------|-----------------------|-----|-------|-------|--------------|-----------------------|-----|-----|-------|--------------|-----------------------|-----|-------|-------|
| Age | Number of | Number of Occurrences | | | | Number of | Number of Occurrences | | | | Number of | Number of Occurrences | | | |
| | Participants | NDPA | PAD | SRD | Total | Participants | NDPA | PAD | SRD | Total | Participants | NDPA | PAD | SRD | Total |
| 17-22 | 19,794 | 14 | 42 | 18 | 74 | 3,330 | - | 3 | | 3 | 6,660 | 2 | 3 | 2 | 7 |
| 23-28 | 12,213 | 11 | 14 | 165 | 190 | 3,460 | - | 3 | 12 | 15 | 9,118 | 13 | | 48 | 61 |
| 29-34 | 20,314 | 19 | 7 | 476 | 502 | 6,714 | 17 | 1 | 56 | 74 | 15,087 | 29 | | 149 | 178 |
| 35-39 | 22,905 | 138 | 2 | 800 | 940 | 10,175 | 97 | | 143 | 240 | 18,241 | 145 | | 253 | 398 |
| 40-45 | 21,694 | 77 | 1 | 733 | 811 | 8,676 | 49 | | 104 | 153 | 20,545 | 127 | | 435 | 562 |
| 46-51 | 21,292 | 176 | 4 | 595 | 775 | 7,715 | 70 | 1 | 122 | 193 | 19,960 | 242 | | 761 | 1,003 |
| 52-57 | 17,839 | 283 | 2 | 452 | 737 | 5,782 | 135 | | 205 | 340 | 10,329 | 265 | | 93 | 358 |
| 59-63 | 6,362 | 305 | | 485 | 790 | 2,213 | 92 | | 183 | 275 | 6,873 | 362 | | 407 | 769 |
| 64-69 | 1,268 | 248 | | 152 | 400 | 636 | 97 | | 66 | 163 | 2,184 | 239 | | 156 | 395 |
| 70-74 | 160 | 68 | | 8 | 76 | 66 | 44 | | 6 | 50 | 443 | 71 | | 11 | 82 |
| Total | 143,841 | 1,339 | 72 | 3,884 | 5,295 | 48,767 | 601 | 8 | 897 | 1,506 | 109,440 | 1,495 | 3 | 2,315 | 3,813 |

- 4. Calculate $q_x^{(j_k)}$, \forall_k which is the new clustering result using Equation (4).
- 5. Determine the initial number of individuals, $l_x^{(\tau)}$, and
 6. Calculate $l_x^{(\tau)}$, calculate $d_x^{(j_k)} = l_x^{(\tau)} q_x^{(j_k)}$, $d_x^{(NDPA)} = \sum_{k=1}^f d_x^{(NDPA_k)}$, $d_x^{(PAD)} = \sum_{k=1}^g d_x^{(PAD_k)}$, $d_x^{(SRD)} = \sum_{k=1}^h d_x^{(SRD_k)}$, and $d_x^{(\tau)} = \sum_{j=1}^3 d_x^{(j)}$ then $l_{x+t}^{(\tau)} = l_x^{(\tau)} d_x^{(\tau)}$. Repeat this step until x = 74.

Based on Figure 2, in general, the credibility cause probability is between observation and TMI IV for each region, except for the R1 region. This shows that exposures other than the R1 region tend to be small so their cause probability are greater than TMI IV. The credibility cause probability can be an alternative pricing. Meanwhile, the R1 region has a fairly large exposure compared to other regions and the odds are smaller for a certain age than TMI IV.

As explained in Chapter 1, there is complexity in calculating probabilities of multiple decrement increase as the number of causes and factors. Therefore,

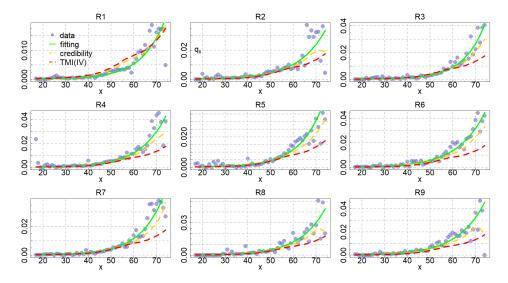


FIGURE 2. Probability of NDPA per age, $q_x^{''(NDPA_k)}$, for R1 - R9

the causes probability are clustered using k-means clustering, especially factors with causes other than death (without reducing the original characteristics). This method is one of the non-hierarchical data clustering methods that seeks to partition existing data into two or more clusters. The purpose of this data clustering is to minimize an objective function which generally seeks to minimize diversity within a cluster and maximize diversity between clusters. To calculate the centroid of the kth cluster, on the jth variable, v_{kj} is used,

$$v_{kj} = \frac{\sum_{i=1}^{N_k} x_{ij}}{N_k} \tag{9}$$

with x_{ij} the observation value of the *i*th object in the *k*th Cluster for the *j*th variable and N_k the number of members of the *k*th cluster [12].

The optimal cluster is determined by the magnitude of the Coefficient of Silhouette which is in [-1,1]. A value close to 1 is the best value. The Silhouette Coefficient is based on geometric considerations of cluster cohesion and separation. Cohesion is used to measure the closeness of objects that are in one cluster and separation is used to measure the closeness between the clusters formed. The Silhouette coefficient of the *i*th object, x_i , is defined,

$$S_{x_i} = \frac{b_{p,i} - a_{p,i}}{\max(a_{p,i}, b_{p,i})}$$

with $a_{p,i}$ the average distance of the *i*th object with all objects in the pth cluster (the same cluster as the *i*th object). As for $b_{p,i}$, the minimum value of $d_{q,i}$, which is the average of the *i*th object with all objects in the *q*th cluster (a cluster that is different from the *i*th object), where $p \neq q$. The value of $b_{p,i}$ shows the average

difference of object i to the cluster closest to its neighbors. If S_{x_i} has a high value, the more appropriate the placement of x_i in cluster p. The Silhouette Coefficient (SLH) value is written,

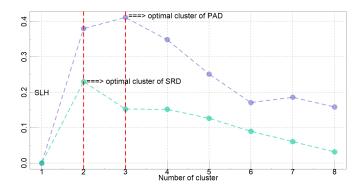


FIGURE 3. SLH of APD (top) and SRD (bottom)

$$SLH = \frac{1}{N} \sum_{i=1}^{N} S_{x_i}$$

with N number of objects. The best clustering is achieved if SLH is maximized which means the distance between objects in the cluster is minimum and the distance between clusters is maximum [13].

In Figure 3, the optimal clusters for PAD causes and SRD causes are 3 (three) and 2 (two) clusters, respectively. Next, K-means clustering is performed for each causes.

Table 2. K-means algorithm

| Input | Parameter k, number of clusters, and x_{ij} , object with dimension $N \times 2$; |
|---------|--|
| Process | 1. Select k objects that will be the initial centroid, v_{kj} ; |
| | 2. Calculate the distance of x_{ij} and v_{kj} using Euclidean Distance; |
| | $d(x_i, v_k) = \sqrt{\sum_{j=1}^{2} (x_{ij} - v_{kj})^2}, \forall i, k;$ |
| | 3. Allocate x_{ij} to the cluster that has the minimum distance to v_{kj} ; |
| | 4. Calculate the cluster centroid for each clusters using Equation (9); and |
| | 5. Repeat step 3 through 5 until no object moves to another cluster. |
| Output | x_{ij} is divided into k clusters |

Based on Figure 4, the clustering results of PAD causes are divided into 3 (three) clusters, namely cluster 1 (R3), cluster 2 (R7), and cluster 3 (R1,R2,R4,R5,

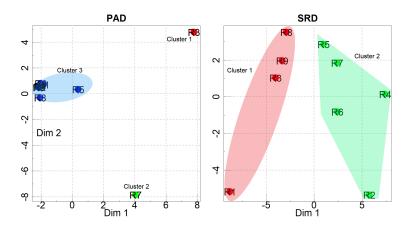


FIGURE 4. Clustering of PAD and SRD for regions

R6,R8,R9). In addition, the clustering results of SRD causes are divided into 2 (two) clusters, namely cluster 1 (R1,R3,R8,R9) and cluster 2 (R2,R4,R5,R6,R7). Thus the causal factors, $NDPA_k$ with $k=R1,R2,\cdots,R9,PAD_k$ with k=C1,C2,C3, and SRD_k with k=D1,D2.

Table 3. Probability of multiple decrement

| | NDD4 | NDDA | NDDA | NDD4 | NDDA | NDDA | NDD 4 | NDDA | NDDA | DAD | DAD | DAD | CDD | CDD |
|-----------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Age | $q_x^{NDPA_{R_1}}$ | $q_x^{NDPA_{R_2}}$ | $q_x^{NDPA_{R_3}}$ | $q_x^{NDPA_{R_4}}$ | $q_x^{NDPA_{R_5}}$ | $q_x^{NDPA_{R_6}}$ | $q_x^{NDPA_{R_7}}$ | $q_x^{NDPA_{R_8}}$ | $q_x^{NDPA_{R_9}}$ | $q_x^{PAD_{C_1}}$ | $q_x^{PAD_{C_2}}$ | $q_x^{PAD_{C_3}}$ | $q_x^{SRD_{D_1}}$ | $q_x^{SRD_{D_2}}$ |
| 17 | 0.00029 | 0.00033 | 0.00031 | 0.00028 | 0.00043 | 0.00033 | 0.00035 | 0.00032 | 0.00033 | 0.00000 | 0.00000 | 0.00091 | 0.00000 | 0.00000 |
| 18 | 0.00032 | 0.00038 | 0.00034 | 0.00031 | 0.00042 | 0.00035 | 0.00037 | 0.00034 | 0.00034 | 0.00000 | 0.00000 | 0.00051 | 0.00000 | 0.00000 |
| 19 | 0.00034 | 0.00043 | 0.00035 | 0.00033 | 0.00041 | 0.00037 | 0.00039 | 0.00035 | 0.00035 | 0.01331 | 0.00000 | 0.00031 | 0.00000 | 0.00000 |
| $\frac{20}{21}$ | 0.00035 | 0.00047 | 0.00037 | 0.00035 | 0.00042 | 0.00039 0.00041 | 0.00042 | 0.00037 | 0.00037 | 0.00304 | 0.00000 | 0.00008 | 0.00013 | 0.00108 0.00390 |
| 21 | 0.00036 0.00037 | 0.00049 0.00051 | 0.00039 0.00041 | 0.00037 0.00039 | 0.00043 0.00046 | 0.00041 | 0.00043 0.00045 | 0.00038 0.00039 | 0.00039 0.00041 | 0.00234 0.00000 | 0.00000 0.00000 | 0.00000 0.00000 | 0.00000 0.00038 | 0.00390 |
| 23 | 0.00037 | 0.00051 | 0.00041 | 0.00039 | 0.00040 | 0.00046 | 0.00045 | 0.00039 | 0.00041 | 0.00000 | 0.00000 | 0.00000 | 0.00065 | 0.00410 |
| 24 | 0.00037 | 0.00054 | 0.00045 | 0.00042 | 0.00043 | 0.00040 | 0.00048 | 0.00041 | 0.00043 | 0.000227 | 0.00000 | 0.00015 | 0.00067 | 0.00132 |
| 25 | 0.00038 | 0.00065 | 0.00047 | 0.00047 | 0.00059 | 0.00055 | 0.00051 | 0.00046 | 0.00057 | 0.00002 | 0.00000 | 0.00003 | 0.00095 | 0.00799 |
| 26 | 0.00040 | 0.00070 | 0.00050 | 0.00051 | 0.00063 | 0.00060 | 0.00054 | 0.00049 | 0.00063 | 0.00043 | 0.00017 | 0.00003 | 0.00057 | 0.00979 |
| 27 | 0.00044 | 0.00074 | 0.00053 | 0.00055 | 0.00065 | 0.00064 | 0.00057 | 0.00054 | 0.00070 | 0.00076 | 0.00000 | 0.00033 | 0.00111 | 0.01018 |
| 28 | 0.00048 | 0.00076 | 0.00056 | 0.00060 | 0.00068 | 0.00068 | 0.00061 | 0.00061 | 0.00075 | 0.00067 | 0.00000 | 0.00009 | 0.00098 | 0.01074 |
| 29 | 0.00052 | 0.00079 | 0.00060 | 0.00066 | 0.00070 | 0.00074 | 0.00065 | 0.00067 | 0.00080 | 0.00000 | 0.00000 | 0.00006 | 0.00129 | 0.01166 |
| 30 | 0.00057 | 0.00083 | 0.00064 | 0.00071 | 0.00073 | 0.00080 | 0.00070 | 0.00074 | 0.00085 | 0.00027 | 0.00000 | 0.00002 | 0.00100 | 0.01242 |
| 31 | 0.00062 | 0.00087 | 0.00068 | 0.00078 | 0.00077 | 0.00086 | 0.00075 | 0.00081 | 0.00090 | 0.00024 | 0.00000 | 0.00003 | 0.00107 | 0.01141 |
| 32 | 0.00067 | 0.00093 | 0.00073 | 0.00084 | 0.00082 | 0.00093 | 0.00080 | 0.00087 | 0.00097 | 0.00022 | 0.00000 | 0.00002 | 0.00143 | 0.01261 |
| 33 | 0.00071 | 0.00099 | 0.00078 | 0.00091 | 0.00087 | 0.00101 | 0.00086 | 0.00093 | 0.00105 | 0.00020 | 0.00000 | 0.00000 | 0.00143 | 0.01269 |
| 34 | 0.00077 | 0.00106 | 0.00084 | 0.00099 | 0.00092 | 0.00111 | 0.00093 | 0.00100 | 0.00114 | 0.00000 | 0.00000 | 0.00000 | 0.00118 | 0.01256 |
| 35 | 0.00083 | 0.00115 | 0.00091 | 0.00107 | 0.00100 | 0.00121 | 0.00101 | 0.00108 | 0.00125 | 0.00000 | 0.00000 | 0.00000 | 0.00122 | 0.01107 |
| 36 | 0.00089 | 0.00125 | 0.00098 | 0.00117 | 0.00109 | 0.00134 | 0.00110 | 0.00119 | 0.00137 | 0.00000 | 0.00000 | 0.00000 | 0.00117 | 0.01007 |
| 37 | 0.00097 | 0.00136 | 0.00106 | 0.00128 | 0.00120 | 0.00148 | 0.00120 | 0.00131 | 0.00151 | 0.00000 | 0.00000 | 0.00000 | 0.00120 | 0.01090 |
| 38 | 0.00105 | 0.00148 | 0.00115 | 0.00141 | 0.00133 | 0.00162 | 0.00131 | 0.00145 | 0.00165 | 0.00000 | 0.00000 | 0.00000 | 0.00151 | 0.01150 |
| 39 40 | 0.00115 0.00127 | 0.00160 0.00173 | 0.00126 0.00138 | 0.00155 0.00170 | 0.00146 0.00161 | 0.00178 0.00195 | 0.00143 0.00157 | 0.00157 0.00172 | 0.00179 0.00197 | 0.00000 0.00012 | 0.00000 0.00000 | 0.00000 0.00000 | 0.00185 0.00106 | 0.01428 0.00765 |
| 41 | 0.00127 | 0.00173 | 0.00158 | 0.00170 | 0.00101 | 0.00193 | 0.00137 | 0.00172 | 0.00197 | 0.00012 | 0.00000 | 0.00000 | 0.00106 | 0.00765 |
| 42 | 0.00140 | 0.00100 | 0.00168 | 0.00103 | 0.00170 | 0.00210 | 0.00171 | 0.00100 | 0.00210 | 0.00010 | 0.00000 | 0.00000 | 0.00117 | 0.01144 |
| 43 | 0.00133 | 0.00202 | 0.00103 | 0.00203 | 0.00132 | 0.00257 | 0.00100 | 0.00203 | 0.00260 | 0.00033 | 0.00000 | 0.00000 | 0.000117 | 0.01104 |
| 44 | 0.00172 | 0.00242 | 0.00206 | 0.00246 | 0.00231 | 0.00280 | 0.00229 | 0.00245 | 0.00284 | 0.00001 | 0.00000 | 0.00000 | 0.00041 | 0.01120 |
| 45 | 0.00210 | 0.00265 | 0.00227 | 0.00271 | 0.00255 | 0.00302 | 0.00252 | 0.00270 | 0.00309 | 0.00000 | 0.00000 | 0.00000 | 0.00477 | 0.01218 |
| 46 | 0.00232 | 0.00292 | 0.00251 | 0.00299 | 0.00282 | 0.00326 | 0.00279 | 0.00297 | 0.00336 | 0.00000 | 0.00000 | 0.00001 | 0.00654 | 0.01169 |
| 47 | 0.00255 | 0.00321 | 0.00279 | 0.00330 | 0.00312 | 0.00355 | 0.00309 | 0.00327 | 0.00367 | 0.00000 | 0.00000 | 0.00000 | 0.00435 | 0.01099 |
| 48 | 0.00280 | 0.00353 | 0.00308 | 0.00363 | 0.00344 | 0.00389 | 0.00341 | 0.00360 | 0.00403 | 0.00000 | 0.00000 | 0.00000 | 0.00125 | 0.01127 |
| 49 | 0.00307 | 0.00385 | 0.00339 | 0.00398 | 0.00378 | 0.00426 | 0.00375 | 0.00395 | 0.00444 | 0.00018 | 0.00000 | 0.00000 | 0.00112 | 0.01255 |
| 50 | 0.00337 | 0.00420 | 0.00372 | 0.00436 | 0.00415 | 0.00467 | 0.00411 | 0.00433 | 0.00488 | 0.00000 | 0.00000 | 0.00000 | 0.00118 | 0.01241 |
| 51 | 0.00370 | 0.00458 | 0.00409 | 0.00478 | 0.00455 | 0.00512 | 0.00452 | 0.00476 | 0.00535 | 0.00000 | 0.00000 | 0.00001 | 0.00098 | 0.01074 |
| 52 | 0.00407 | 0.00499 | 0.00448 | 0.00523 | 0.00499 | 0.00561 | 0.00495 | 0.00524 | 0.00584 | 0.00022 | 0.00000 | 0.00001 | 0.00091 | 0.01036 |
| 53 | 0.00446 | 0.00542 | 0.00490 | 0.00571 | 0.00546 | 0.00612 | 0.00540 | 0.00575 | 0.00635 | 0.00023 | 0.00000 | 0.00000 | 0.00108 | 0.01150 |
| 54 55 | 0.00489 0.00532 | 0.00587 0.00635 | 0.00535 0.00582 | 0.00622 0.00676 | 0.00597 0.00651 | 0.00669 0.00730 | 0.00589 0.00640 | 0.00628 0.00682 | 0.00689 0.00748 | 0.00000 0.00000 | 0.00000 0.00000 | 0.00000 0.00000 | 0.00118 0.00136 | 0.01067 0.01052 |
| 56 | 0.00532 | 0.00683 | 0.00582 | 0.00773 | 0.00708 | 0.00736 | 0.00693 | 0.00032 | 0.00748 | 0.00000 | 0.00000 | 0.00000 | 0.00130 | 0.01032 |
| 57 | 0.00617 | 0.00731 | 0.00681 | 0.00790 | 0.00768 | 0.00730 | 0.00748 | 0.00794 | 0.00813 | 0.00000 | 0.00000 | 0.00000 | 0.00121 | 0.00931 |
| 58 | 0.00653 | 0.00776 | 0.00731 | 0.00849 | 0.00830 | 0.00935 | 0.00802 | 0.00154 | 0.00953 | 0.00000 | 0.00000 | 0.00000 | 0.00274 | 0.01065 |
| 59 | 0.00683 | 0.00819 | 0.00779 | 0.00907 | 0.00893 | 0.01003 | 0.00855 | 0.00915 | 0.01020 | 0.00000 | 0.00000 | 0.00000 | 0.00653 | 0.01520 |
| 60 | 0.00710 | 0.00866 | 0.00831 | 0.00968 | 0.00959 | 0.01070 | 0.00910 | 0.00976 | 0.01086 | 0.00000 | 0.00000 | 0.00000 | 0.00850 | 0.01959 |
| 61 | 0.00736 | 0.00919 | 0.00887 | 0.01034 | 0.01031 | 0.01137 | 0.00968 | 0.01041 | 0.01155 | 0.00000 | 0.00000 | 0.00000 | 0.01259 | 0.01890 |
| 62 | 0.00767 | 0.00983 | 0.00950 | 0.01105 | 0.01110 | 0.01208 | 0.01036 | 0.01116 | 0.01232 | 0.00000 | 0.00000 | 0.00000 | 0.01261 | 0.01750 |
| 63 | 0.00805 | 0.01062 | 0.01024 | 0.01189 | 0.01195 | 0.01290 | 0.01119 | 0.01204 | 0.01318 | 0.00000 | 0.00000 | 0.00000 | 0.01132 | 0.01461 |
| 64 | 0.00849 | 0.01153 | 0.01109 | 0.01292 | 0.01286 | 0.01384 | 0.01219 | 0.01300 | 0.01408 | 0.00000 | 0.00000 | 0.00006 | 0.00935 | 0.01408 |
| 65 | 0.00899 | 0.01260 | 0.01208 | 0.01419 | 0.01383 | 0.01499 | 0.01335 | 0.01405 | 0.01508 | 0.00000 | 0.00000 | 0.00000 | 0.00903 | 0.01176 |
| 66 | 0.00953 | 0.01366 | 0.01314 | 0.01564 | 0.01482 | 0.01625 | 0.01454 | 0.01515 | 0.01615 | 0.00000 | 0.00000 | 0.00000 | 0.01318 | 0.01308 |
| 67 | 0.01020 | 0.01477 | 0.01443 | 0.01732 | 0.01605 | 0.01775 | 0.01585 | 0.01657 | 0.01748 | 0.00000 | 0.00000 | 0.00000 | 0.00901 | 0.01170 |
| 68 | 0.01092 | 0.01580 | 0.01580 | 0.01895 | 0.01737 | 0.01936 | 0.01718 | 0.01809 | 0.01906 | 0.00000 | 0.00000 | 0.00000 | 0.00795 | 0.01072 |
| 69 | 0.01173 | 0.01673 | 0.01738 | 0.02054 | 0.01887 | 0.02106 | 0.01870 | 0.01972 | 0.02067 | 0.00000 | 0.00000 | 0.00000 | 0.00544 | 0.00825 |
| 70 71 | 0.01257 | 0.01740 | 0.01909 | 0.02186 | 0.02036 | 0.02264 | 0.02045 | 0.02108 | 0.02172 | 0.00000 | 0.00000 | 0.00000 | 0.00594 | 0.00915 |
| $\frac{71}{72}$ | 0.01351 0.01450 | 0.01783 0.01793 | 0.02095 0.02292 | 0.02303 0.02413 | 0.02204 0.02401 | 0.02423 0.02595 | 0.02274 0.02573 | 0.02187 0.02195 | 0.02195 0.02080 | 0.00000 0.00000 | 0.00000 | 0.00000 0.00000 | 0.00332 0.00372 | 0.00744 0.00343 |
| 73 | 0.01450 | 0.01793 | 0.02292 | 0.02413 | 0.02401 | 0.02595 | 0.02938 | 0.02195 | 0.02080 | 0.00000 | 0.00000 | 0.00000 | 0.00372 | 0.00343 0.00523 |
| 74 | 0.01548 | 0.01750 | 0.02481 | 0.02683 | 0.02823 | 0.02770 | 0.02938 | 0.02090 | 0.01654 | 0.00000 | 0.00000 | 0.00000 | 0.00439 | 0.00525 |
| 14 | 0.01039 | 0.01090 | 0.02089 | 0.02083 | 0.02023 | 0.02908 | 0.05527 | 0.01932 | 0.01034 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00101 |

In Table 3, the decrement probability of each cause per factor that has been clustered is obtained. In accordance with Subsection 2.2 that the ASD opportunity is greater than the MD opportunity obtained. As for Table 4, the initial group of 17 years old is simulated as many as 100000 and the remaining 1922 at the age of 74 years.

Table 4. Multiple decrement table

| Age | l_x^{τ} | $d_x^{NDPA_{R_1}}$ | $d_x^{NDPA_{R_2}}$ | $d_x^{NDPA_{R_3}}$ | $d_x^{NDPA_{R_4}}$ | $d_x^{NDPA_{R_5}}$ | $d_x^{NDPA_{R_6}}$ | $d_x^{NDPA_{R_7}}$ | $d_x^{NDPA_{R_8}}$ | $d_x^{NDPA_{R_9}}$ | $d_x^{PAD_{C_1}}$ | $d_x^{PAD_{C_2}}$ | $d_x^{PAD_{C_3}}$ | $d_x^{SRD_{D_1}}$ | $d_x^{SRD_{D_2}}$ |
|-----------------|------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| 17 | 100,000 | 29 | 33 | 31 | 28 | 43 | 33 | 35 | 32 | 33 | 0 | 0 | 91 | 0 | 0 |
| 18 | 99,613 | 31 | 38 | 33 | 31 | 42 | 35 | 37 | 33 | 34 | 0 | 0 | 51 | 0 | 0 |
| 19 | 99,247 | 33 | 43 | 35 | 33 | 41 | 36 | 39 | 35 | 35 | 1,321 | 0 | 31 | 0 | 0 |
| 20 | 97,565 | 35 | 46 | 37 | 34 | 41 | 38 | 41 | 36 | 36 | 297 | 0 | 8 | 13 | 105 |
| 21 | 96,800 | 35 | 48 | 38 | 36 | 42 | 39 | 42 | 37 | 37 | 226 | 0 | 0 | 0 | 377 |
| $\frac{22}{23}$ | 95,842 95,046 | 35 35 | 49 52 | 39 40 | 38 40 | 44 47 | 41 44 | 43 44 | 38 39 | 40 43 | 0 215 | 0 | 0 12 | 36 61 | 393 753 |
| 24 | 93,621 | 35 | 55 | 42 | 41 | 51 | 47 | 45 | 40 | 47 | 58 | 0 | 5 | 63 | 770 |
| 25 | 92,322 | 35 | 60 | 44 | 44 | 54 | 51 | 47 | 42 | 52 | 0 | 0 | 11 | 88 | 737 |
| 26 | 91,058 | 37 | 64 | 45 | 46 | 57 | 55 | 49 | 45 | 57 | 40 | 16 | 3 | 52 | 891 |
| 27 | 89,601 | 39 | 66 | 47 | 50 | 58 | 58 | 51 | 49 | 62 | 68 | 0 | 29 | 99 | 912 |
| 28 | 88,013 | 42 | 67 | 49 | 53 | 60 | 60 | 53 | 53 | 66 | 59 | 0 | 8 | 86 | 946 |
| 29 | 86,411 | 45 | 69 | 52 | 57 | 60 | 64 | 56 | 58 | 69 | 0 | 0 | 5 | 112 | 1,007 |
| 30 | 84,757 | 48 | 70 | 54 | 61 | 62 | 67 | 59 | 63 | 72 | 23 | 0 | 2 | 85 | 1,053 |
| $\frac{31}{32}$ | 83,039 81,394 | 51 54 | 73 76 | 57 60 | 65 69 | 64 67 | 72 76 | 62 65 | 67 71 | 75 79 | 20 18 | 0 | 3 | 89 117 | 947 1,026 |
| 33 | 79,617 | 54 57 | 79 | 62 | 73 | 69 | 81 | 69 | 71 | 83 | 16 | 0 | 1 0 | 117 | 1,026 |
| 34 | 77,830 | 60 | 83 | 66 | 77 | 72 | 86 | 73 | 78 | 89 | 0 | 0 | 0 | 92 | 977 |
| 35 | 76,078 | 63 | 87 | 69 | 82 | 76 | 92 | 77 | 82 | 95 | 0 | 0 | 0 | 92 | 842 |
| 36 | 74,419 | 66 | 93 | 73 | 87 | 81 | 100 | 82 | 88 | 102 | 0 | 0 | 0 | 87 | 749 |
| 37 | 72,810 | 70 | 99 | 77 | 93 | 88 | 107 | 87 | 96 | 110 | 0 | 0 | 0 | 87 | 794 |
| 38 | 71,102 | 75 | 105 | 82 | 100 | 94 | 115 | 93 | 103 | 117 | 0 | 0 | 0 | 108 | 818 |
| 39 | 69,292 | 80 | 111 | 87 | 107 | 101 | 123 | 99 | 109 | 124 | 0 | 0 | 0 | 128 | 989 |
| 40 | 67,233 | 85 | 116 | 93 | 114 | 108 | 131 | 105 | 115 | 133 | 8 | 0 | 0 | 72 | 515 |
| $\frac{41}{42}$ | 65,637 63,730 | 92 99 | 122 129 | 100 107 | 121 129 | 115 122 | 142 151 | 112 120 | 122 129 | 142 151 | 11 21 | 0 | 0 | 77 75 | 751 742 |
| 43 | 61,754 | 106 | 136 | 115 | 138 | 130 | 160 | 128 | 137 | 161 | 10 | 0 | 0 | 25 | 695 |
| 44 | 59,812 | 114 | 145 | 123 | 147 | 139 | 167 | 137 | 147 | 170 | 0 | 0 | 1 | 103 | 616 |
| 45 | 57,804 | 122 | 153 | 131 | 156 | 148 | 174 | 146 | 156 | 179 | ő | 0 | 0 | 275 | 704 |
| 46 | 55,460 | 129 | 162 | 139 | 166 | 156 | 181 | 155 | 165 | 186 | 0 | 0 | 1 | 363 | 649 |
| 47 | 53,010 | 135 | 170 | 148 | 175 | 165 | 188 | 164 | 173 | 195 | 0 | 0 | 0 | 230 | 583 |
| 48 | 50,684 | 142 | 179 | 156 | 184 | 174 | 197 | 173 | 182 | 204 | 0 | 0 | 0 | 63 | 571 |
| 49 | 48,457 | 149 | 187 | 164 | 193 | 183 | 206 | 181 | 191 | 215 | 9 | 0 | 0 | 54 | 608 |
| 50 51 | 46,116 43,746 | 155 162 | 194 200 | 172 179 | 201 209 | 191 199 | 215 224 | 190 198 | 200 208 | 225 234 | 0 | 0 | 0 | 55 43 | 573 470 |
| 52 | 41,419 | 169 | 207 | 186 | 216 | 207 | 232 | 205 | 217 | 242 | 9 | 0 | 1 | 38 | 429 |
| 53 | 39,062 | 174 | 212 | 192 | 223 | 213 | 239 | 211 | 224 | 248 | 9 | 0 | 0 | 42 | 449 |
| 54 | 36,626 | 179 | 215 | 196 | 228 | 219 | 245 | 216 | 230 | 252 | 0 | 0 | 0 | 43 | 391 |
| 55 | 34,212 | 182 | 217 | 199 | 231 | 223 | 250 | 219 | 233 | 256 | 0 | 0 | 0 | 46 | 360 |
| 56 | 31,795 | 183 | 217 | 201 | 233 | 225 | 253 | 220 | 234 | 259 | 0 | 0 | 0 | 39 | 315 |
| 57 | 29,417 | 181 | 215 | 200 | 233 | 226 | 254 | 220 | 234 | 260 | 0 | 0 | 0 | 33 | 269 |
| 58 | 27,092 | 177 | 210 | 198 | 230 | 225 | 253 | 217 | 232 | 258 | 0 | 0 | 1 | 74 | 289 |
| 59 | 24,729 | 169 | 203 | 193 | 224 | 221 | 248 | 211 | 226 | 252 | 0 | 0 | 0 | 162 | 376 |
| 60 61 | 22,244 19,756 | 158 145 | 193 181 | 185 175 | 215 204 | 213 204 | 238 225 | 202 191 | 217 206 | 242 228 | 0 | 0 | 0 | 189 249 | 436 373 |
| 62 | 17,374 | 133 | 171 | 165 | 192 | 193 | 210 | 180 | 194 | 214 | 0 | 0 | 0 | 219 | 304 |
| 63 | 15,199 | 122 | 161 | 156 | 181 | 182 | 196 | 170 | 183 | 200 | 0 | 0 | 0 | 172 | 222 |
| 64 | 13,254 | 112 | 153 | 147 | 171 | 170 | 183 | 162 | 172 | 187 | 0 | 0 | 1 | 124 | 187 |
| 65 | 11,485 | 103 | 145 | 139 | 163 | 159 | 172 | 153 | 161 | 173 | 0 | 0 | 0 | 104 | 135 |
| 66 | 9,877 | 94 | 135 | 130 | 155 | 146 | 160 | 144 | 150 | 160 | 0 | 0 | 0 | 130 | 129 |
| 67 | 8,345 | 85 | 123 | 120 | 145 | 134 | 148 | 132 | 138 | 146 | 0 | 0 | 0 | 75 | 98 |
| 68 | 7,000 | 76 | 111 | 111 | 133 | 122 | 136 | 120 | 127 | 133 | 0 | 0 | 0 | 56 | 75 |
| 69 | 5,802 | 68 | 97 | 101 | 119 | 110 | 122 | 108 | 114 | 120 | 0 | 0 | 0 | 32 | 48 |
| 70 71 | 4,762 $3,847$ | 60 52 | 83 69 | 91 81 | 104 89 | 97 85 | 108 93 | 97 87 | 100 84 | 103 84 | 0 | 0 | 0 | 28 13 | 44 29 |
| 72 | 3,082 | 52 45 | 55 | 71 | 74 | 89 74 | 93 80 | 79 | 68 | 64 64 | 0 | 0 | 0 | 13 | 29 11 |
| 73 | 2,450 | 38 | 43 | 61 | 62 | 64 | 68 | 72 | 51 | 45 | 0 | 0 | 0 | 11 | 13 |
| 74 | 1,922 | 32 | 33 | 52 | 52 | 54 | 57 | 64 | 37 | 32 | 0 | 0 | 0 | 0 | 3 |
| 1.4 | 1,022 | 32 | 33 | - 02 | 32 | 54 | 31 | 04 | 31 | 32 | U | U | U | U | 0 |

4. Conclusions

The Companies, especially insurance companies, can construct multiple decrement tables according to their experience by considering certain factors, such as region and others. The results of the company study tend to be smaller than the industry (TMI IV 2019). This is due to the smaller exposure of the company compared to the industry. Credibility theory can be utilized to obtain a weighted rate between the industry and the company.

The cause probability without considering other causes (Associated Single Decrement) is greater than the cause probability considering other causes (Multiple Decrement). Factor clustering needs to be done first to reduce the computational complexity of calculating the cause probability. The results of this study can be utilized as pricing and reserving of insurance companies.

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